Analysis and Management of Security Constraints in Overstressed Power Systems

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Abstract

Management of operational security constraints is one of the important tasks performed by system operators, which must be addressed properly for secure and economic operation. Constraint management is becoming an increasingly complex and challenging to execute in modern electricity networks for three main reasons. First, insufficient transmission capacity during peak and emergency conditions, which typically result in numerous constraint violations. Second, reduced fault levels, inertia and damping due to power electronic interfaced demand and stochastic renewable generation, which are making network more vulnerable to even small disturbances. Third, re-regulated electricity markets require the networks to operate much closer to their operational security limits, which typically result in stressed and overstressed operating conditions.

Operational security constraints can be divided into static security limits (bus voltage and branch thermal limits) and dynamic security limits (voltage and angle stability limits). Security constraint management, in general, is formulated as a constrained, nonlinear, and nonconvex optimization problem. The problem is usually solved by conventional gradient-based nonlinear programming methods to devise optimal non-emergency or emergency corrective actions utilizing minimal system reserves. When the network is in emergency state with reduced/insufficient control capability, the solution space of the corresponding nonlinear optimization problem may be too small, or even infeasible. In such cases, conventional nonlinear programming methods may fail to compute a feasible (corrective) control solution that mitigate all constraint violations or might fail to rationalize a large number of immediate post-contingency constraint violations into a smaller number of critical constraints.

Although there exists some work on devising corrective actions for voltage and thermal congestion management, this has mostly focused on the alert state of the operation, not on the overstressed and emergency conditions, where, if appropriate control actions are not taken, network may lose its integrity. As it will be difficult for a system operator to manage a large number of constraint violations (e.g. more than ten) at one time, it is very important to rationalize the violated constraints to a

minimum subset of critical constraints and then use information on their type and location to implement the right corrective actions at the right locations, requiring minimal system reserves and switching operations. Hence, network operators and network planners should be equipped with intelligent computational tools to “filter out” the most critical constraints when the feasible solution space is empty and to provide a feasible control solution when the solution space is too narrow.

With an aim to address these operational difficulties and challenges, this PhD thesis presents three novel interdependent frameworks: Infeasibility Diagnosis and Resolution Framework (IDRF), Constraint Rationalization Framework (CRF) and Remedial Action Selection and Implementation Framework (RASIF). IDRF presents a metaheuristic methodology to localise and resolve infeasibility in constraint management problem formulations (in specific) and nonlinear optimization problem formulations (in general). CRF extends PIDRF and reduces many immediate post-contingency constraint violations into a small number of critical constraints, according to various operational priorities during overstressed operating conditions. Each operational priority is modelled as a separate objective function and the formulation can be easily extended to include other operational aspects.

Based on the developed CRF, RASIF presents a methodology for optimal selection and implementation of the most effective remedial actions utilizing various ancillary services, such as distributed generation control, reactive power compensation, demand side management, load shedding strategies. The target buses for the implementation of the selected remedial actions are identified using bus active and reactive power injection sensitivity factors, corresponding to the overloaded lines and buses with excessive voltage violations (i.e. critical constraints). The RASIF is validated through both static and dynamic simulations to check the satisfiability of dynamic security constraints during the transition and static security constraints after the transition. The obtained results demonstrate that the framework for implementation of remedial actions allows the most secure transition between the pre-contingency and post-contingency stable equilibrium points.

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own, except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification, except as specified.

Jagadeesh Gunda

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Dedication

I would like to dedicate this thesis to my parents (Komuraiah and Rajeshwari) and my brother Sampath Gunda. Although my parents were illiterate and come from a poor family, they did more than they can do for me to reach this position. My existence is nothing without them. The academic excellence and successes of my brother have played a substantial role in nurturing my academic voyage. I am extremely thankful to him for being my academic role model.

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Acronyms and Abbreviations

APOL	Aggregated Percentage Overloading
APVV	Aggregated Percentage of voltage Violation
AVR	Automatic Voltage Regulator
BPF	Barrier Penalty Functions
CANECC	Cost of Available Non-emergency Corrective Controls
CC	Critical Constraints
CCG	Critical Constraint Group
CCS	Critical Constraint Set
CCV	Critical Constraint Violation
CI	Constant Impedance Load Model
CM	Congestion Management
COCF	Critical Operating Constraint Framework
CP	Constant Power Load Model
CR	Constraint Relaxation
CRF	Constraint Rationalization Framework
CZ	Constant Impedance Load Model
DG	Distributed Generation
DL	Disconnected Load
DSM	Demand Side Management
DynPF	Dynamic Penalty Factors
ECC	Emergency Corrective Controls
FACTS	Flexible AC Transmission Systems
FixPF	Fixed Penalty Factor
FV	Flat Voltage
GA	Genetic Algorithm

HLS	Hard Load Shedding
IC1	Infeasible Contingency
IDRF	Infeasibility Diagnosis and Resolution Framework
IdxCV	Indices of Violated Constraints
IIS	Irreducible Inconsistent Subsystem
IM	Infeasibility Measure
IPAM	Interior Point Algorithm from Matlab
ISF	Injection Sensitivity Factor
ISO	Independent System Operator
KKT	Karush Kuhn Tucker Conditions
LPF	Linear Penalty Functions
MaxNCC	Maximum number of critical constraints
MaxPCS	Maximum number of problematic constraint s
MinNCC	Minimum Number of Non-Critical Constraints
MinPCS	Minimum Most Size of Problematic Constraint Set
MIPS	Matlab Interior Point Solver
MISC	Minimum Intractable Subsystem of Constraints
NCC	Noncritical Constraints
NCCS	Noncritical Constraint Set
NCCV	Noncritical Constraint Violations
NECC	Non-emergency Corrective Controls
NINF	Number of Infeasibilities
NRPF	Newton Raphson Power Flow
OFC	Original Fuel Cost
OLS	Optimal Load Shedding
OLTC	Onload Tap Changer
OOF	Original Objective Function

OPF	Optimal Power Flow
PC	Penalty Cost
PCS	Problematic Constraint Set
PDIPM	Primal Dual Interior Point Method
PFC	Penalized Fuel Cost
POF	Penalized Objective Function
POL	Percentage Overloading
PSO	Particle Swarm Optimization
PSSE	Power System Simulation Software for Engineers
PVV	Percentage Voltage Violation
QPF	Quadratic Penalty Functions
RAS	Remedial Action Schemes
RASIF	Remedial Action Selection and Implementation Framework
SA	Simulated Annealing
SCM	Security Constraint Management
SCOPF	Security Constrained Optimal Power Flow
SCPDIPM	Step Controlled Primal Dual Interior Point Method
SINF	Sum of Infeasibilities
SOLS	Selected Optimal Load Shedding
SPF	Step Penalty Functions
SPINF	Sum of Percentage of Infeasibilities
SPS	Special Protection Systems
SSINF	Sum of Squares of Infeasibilities
TNSCV	Total Number of Security Constraint Violations
TRALM	Trust Region Based Augmented Lagrangian Method
TSO	Transmission System Operator
VVC	Voltage and Var Control

Nomenclature

Variables:

x, u	State and control variables
P_{Gi}, Q_{Gi}	Real and reactive power output of generating unit i
P_{Di}, Q_{Di}	Real and reactive demand at bus i
V_i, θ_i	Voltage magnitude and phase angle at bus i
c	Contingency index, zero for base case
C	Set of credible contingencies

Functions:

f	Objective function
g, h	Equality and inequality constraint functions
F_T, E_T	Total fuel cost and total emission
P_{loss}	Total active power loss
F_p	Penalized objective function
Φ_{eq}, Φ_{ineq}	Penalty functions for equality/inequality constraints

Constants:

$a_i, b_i,\ c_i$	Fuel cost coefficients of generating unit i
d_i, e_i, f_i	Emission coefficients of generating unit i
N_B, N_G, N_L	Number of buses, generators and branches
G_{ij}	Conductance of a line connecting buses i and j
p_v	Penalty for violating bus voltage constraints
p_p	Penalty for violating active power generation limit
p_q	Penalty for violating reactive power generation limit
p_s	Penalty for violating branch MVA constraints
N_{pop}	Number of particles or populations
N_{itr}	Maximum number of iterations or generations
c_1, c_2	Acceleration coefficients for PSO
w_i, w_f	Initial and final inertia weight for PSO
P_c	Crossover probability for GA
T_0	Initial Temperature for SA

Chapter 1
Introduction

This introductory chapter provides a general overview of the thesis. It discusses the motivation and objectives followed by contributions of the thesis.

1.1 Introduction

Planning and operation of modern electricity networks are becoming an increasingly complex task. While the network designers must analyse several relevant technical and non-technical operating conditions during the planning stage, the network operator should operate their networks closer to their operational security limits. This is to meet the requirements of re-regulated market's and to cope with increased uncertainties associated with changing type and nature of demand and renewable generation. These security limits are typically expressed as bus voltage and branch thermal limits (i.e. steady state security limits), as well as voltage and angle stability limits (i.e. dynamic security limits). A secure system must always satisfy static security limits at all steady states and dynamic security limits during the transition between any two successive steady states. Violation of any security limit may constrain the power flow or power transmission across the corresponding buses.

The management of the security constraints, involving their identification and corrective actions, is commonly referred to as security constraint management (SCM) [1], which is one of the critical tasks performed by network operators and planners and is usually formulated as a nonlinear constrained optimization problem.

1.2 Need for Advanced Computational Tools for SCM

Electricity networks are one of the most complex man-made systems. They were designed and built decades ago, according to the existing and projected power flows at that time, which means the large centralized generation was planned and installed to follow the direction of load growth. However, the generation in modern electricity networks is now changing its direction to load, due to the increased penetration of renewable generation, both at transmission and distribution levels. This frequently results in a situation in which the demand in a specific area cannot be offset by the local generation and the (apparent)power flow into that area is limited by the corresponding flowgate/branch capacity. In addition, the operators are forced to operate the networks closer to their operational security limits, in order to defer network investments and maximize the benefit in the re-regulated electricity market.

- Unlike conventional synchronous generators which are electromechanically coupled together and to the network, most of the distributed generators are coupled only electrically via power electronic interface. Across the world (especially in developed countries), conventional power stations are either getting closed or their share is getting down to meet the sustainable energy goals and to provide the room for (decentralised) renewable generation. This has resulted in the reduction of inertia, damping and fault levels in modern electricity networks. Moreover, the low-frequency electromechanical oscillations among the conventional/synchronous generators (which were previously damped effectively) may not be damped effectively under the reduced inertia and damping environment. Hence, modern electricity networks are more vulnerable to even small disturbances as these disturbances could propagate to a larger distance or they could even lead to system instability under the presence of low-frequency oscillations.

In prevailing industrial terminology, SCM, as a process of analysing and adjusting controls to mitigate steady state and dynamic security limits, can be further divided into congestion management (CM) and volt-var control (VVC). SCM process typically involves two stages: a) identification of violated security constraints, and b) activation of appropriate corrective actions for resolving violated constraints.

If the existing control reserves, following a disturbance, are not sufficient to realize a feasible generation dispatch for which all security constraints are satisfied, the network will be forced to operate with many branch thermal violations (overloads) and bus under/over voltages. This particular state of operation is considered as an overstressed operating condition in this thesis and is a part of emergency operating state.

System corrective controls to mitigate constraint violations can be classified into non-emergency corrective controls (NECC) and emergency corrective controls (ECC). ECCs are called only when all NECC are last and/or inefficient to resolve constraint violations. Stressed operating condition is characterised by the violation of at least one security constraint and several other constraints are close to their allowable limits but all the constraint violations can be mitigated through available NECC. Overstressed operating conditions involve violation of at least one security constraint which cannot be resolved by any available NECC.

Under these overstressed operating conditions, if proper emergency control action is not promptly activated, the protection system could trip the corresponding overloaded lines and transformers, as well as disconnect under/over voltage (generator or load) buses which may finally lead to instability.

Calling for additional reserves across many network locations may not be the effective way to resolve congestions both from economic and technical viewpoints. The activation of reserves at many locations implies higher operational costs, resulting in increased electricity prices. Furthermore, increased switching actions may build adverse network dynamic effects, rather than aiding the (over)stressed system.

The SCM is formulated as a nonlinear constrained optimization problem and is usually solved using conventional (deterministic) gradient-based numerical approximation algorithms. These algorithms, though robust, when dealing with overstressed operating conditions may fail to find a feasible solution for supplying all connected customers, even if there is one, or unable to identify the critical operating constraints, if there is no such feasible solution.

Hence, system operators and planners should be equipped with advanced computational tools to diagnose the overstressed operating conditions, rationalize the critical operating constraints from many violated constraints, devise and implement the effective remedial actions (e.g. using available emergency reserves or ancillary services). Such a tool can enhance the decision-making capability at control centres. Even if the last recourse to prevent the network instability is load shedding, such a tool will help operators to find the most optimal locations and amounts of the load to shed. One of the main aims of this thesis is development of a general computational framework that will allow to address operational difficulties and challenges related to overstressed power supply systems.

1.3 Research Motivation and Objectives

The motivation for the presented work was driven by the three following main aspects.

a) While most of the earlier research in power system optimization has focused on developing efficient algorithms for the optimization of feasible mathematical models, little attention has been paid to diagnose or localize the infeasibility in nonlinear optimization models in power system engineering. For example, the nonconvergence of OPF algorithms due to infeasibility is a quite common issue [2] and is still insufficiently addressed in open literature [3]. Although there exist methods to diagnose the infeasibility in linear optimization models, there is no commonly accepted method to diagnose the infeasibility in nonlinear optimization models (in general) and constraint management problem formulations (in specific) [4]-[6]. From the system planning and operation viewpoints, infeasibility localization is especially important, as it helps finding the critical assets in the system.

b) Although extensive efforts are made on solving power system optimization problems using metaheuristic algorithms, their practical implementation is still underway, even for the offline analysis in commercial power system simulators [7]. Moreover, most of the existing metaheuristic methods are focused on optimizing an objective function over feasible search spaces, rather than infeasible search spaces. Being stochastic in nature, metaheuristic algorithms in these cases may be better than conventional methods in diagnosing infeasibility.

c) The vector space spanned by the available controls at a specific time is denoted as the control space of the system at that time. These controls could be preventive or corrective, and corrective controls could be nonemergency or emergency controls. Fundamentally, the system operating condition (and therefore security of the system) at any time depends on the domain of this control space. While a non-empty (i.e. feasible) space indicates the ability of the system to mitigate all active constraint violations, an empty (i.e. infeasible) control space indicates the inability of the system in mitigating all active constraint violations. Accordingly, an infeasible control space situation is considered as the overstressed operating condition in this thesis.

While most of the previous work on constraint management has focused on mitigating constraints during feasible control space situations, limited work exists in the open literature on mitigating constraint violations for infeasible control spaces. Some of the transmission constraints are non-manageable during overstressed operating conditions due to insufficient control capability. In these cases, the trivial solution is to increase the dimension of the control space by adding emergency reserves (so-called remedial actions): addition of some extra or disconnection of some existing active and/or reactive generation, network reconfiguration, demand side management, load shedding, etc.

Most of the existing remedial actions are developed in offline studies and configured to specific events with a fixed level of control. In other words, they are activated by the predefined events, rather than the critical reasoning of the situations and corresponding consequences. Moreover, these actions are entirely focused on technical feasibility and pay no or very small attention to the economic feasibility of the solution. Hence, there is a need to devise and implement remedial actions as and when required with adjustable control capability.

Given the above motivations, the main objective of the thesis is to develop a computational framework that could help operators in managing the violated security constraints, especially during overstressed system operating conditions, and in that way improve the decision-making capability at control centres.

1.4 Problem Statement and Contributions

The research work presented in this thesis aims to answer following general question:

Considering an electricity network which is already operating, or expected to operate under stressed and overstressed conditions, with many active constraint violations and with exhausted controls, how can we select and implement optimal and most effective remedial actions at minimal locations with minimal emergency reserves and with minimal switching actions?

In this perspective, this thesis provides the following contributions:

a) **Infeasibility Diagnosis and Resolution Framework (IDRF):** IDRF presents a metaheuristic methodology to localize and resolve infeasibility in nonlinear optimization problem formulations (in general) and in constraint management problem formulations (in specific).

b) **Constraint Rationalization Framework (CRF):** Effectively, CRF extends IDRF and reduces number of many immediate post-contingency constraint violations into a small number of critical constraints, according to various operational priorities during the overstressed operating conditions. Each operational priority is modelled as a separate objective function and the presented formulation can be easily extended to include other operational aspects.

c) **Remedial Action Selection and Implementation Framework (RASIF):** Based on the developed CRF, RASIF presents a methodology for optimal selection and implementation of the most effective remedial actions, utilizing various ancillary services, such as reactive power compensation, distributed generation control, demand side management and load shedding strategies.

The results from the research in this thesis have been published in seven conference papers [7]-[13] and one Journal paper [14]. Moreover, two journal papers [15-[16] are in preparation. I am the lead author and main contributor to all these publications.

1.5 Research Methodology and Scope

The research methodology is executed in four sequential phases: 1) problem modelling phase, 2) infeasibility analysis phase, 3) constraint rationalization phase and 4) remedial action implementation phase.

Problem modelling phase: In this phase, SCM problem is formulated as a nonlinear constrained optimization problem and a set of mathematically feasible and infeasible operating conditions are created on various IEEE test systems. Based on the resulting optimization formulations, SCM problems are divided into two types: manageable/feasible and non-manageable/infeasible SCM cases. In general, an optimization problem becomes infeasible if there is no solution satisfying all the constraints. The minimal subset of constraints that causes a conventional algorithm to report infeasibility is named as the *minimal intractable subset of constraints (MISC)* [17]. In the context of power supply system analysis in this thesis, MISC is denoted as the *critical operating constraint set (CCS)* and its members are designated as *critical operating constraints (CCs,)* as these constraints restrict the operator to devise a feasible dispatch that satisfies all the security limits. While MISC is defined mainly for the purpose of diagnosing and resolving infeasibility from a “mathematical sense”, the CCS is defined to find the “bottlenecks” in the power system.

Feasibility analysis phase: This phase focuses on solving both types of SCM problems using conventional and metaheuristic algorithms. It demonstrates that conventional algorithms, though robust, are unable to solve and debug the infeasible SCM models. It also reveals that metaheuristic algorithms may be able to resolve the infeasible models in terms of identifying the most critical non-satisfiable constraints (i.e. MISC). As the critical constraints are the root causes for the infeasibility, an infeasible SCM model can be made feasible by removing or relaxing these critical constraints. Based on this fact, an infeasibility diagnosis and resolution framework (IDRF), using modified metaheuristic algorithms and constraint handling functions, is developed to localize and resolve infeasibility.

Constraint rationalization phase: While for a given infeasible operational point the size and index of MISC are unique from pure infeasibility viewpoint (i.e. with infeasibility suitably formulated as an objective function), the size and index of the critical constraint set can be varied based on the operational priorities or objectives of the system operator and economic/market conditions at a given time. For example, the system operator may want to find critical constraint set corresponding to the specific objective function: maximization of lead-time for the next line outage due to the thermal violation. The identification of the locations and causes of critical operating constraints is particularly important as they are crucial in helping system planners and operators in deciding the location, type and amount of controls/reserves to be implemented to return the system into a feasible operating region (maintain system integrity). Given this fact, a novel constraint rationalization framework (CRF) is developed in this phase to compute the critical constraint set corresponding to five distinctive types of operational priorities. However, it should be noted that the introduced CRF framework can be easily extended to other operational priorities, as required or suitable.

Remedial action implementation phase: This phase focuses on devising most effective remedial actions to mitigate constraint violations during overstressed operating conditions (i.e. infeasible SCM cases). A novel remedial action selection and implementation framework (RASIF) is developed for optimal selection and implementation of these most effective remedial actions for resolving constraint violations in infeasible SCM cases. Four types of remedial actions: reactive compensation, distributed generation control, demand-side-management, and load shedding are analysed. The reactive compensation that employed here as the remedial action falls under the emergency corrective controls and is used only when the non-emergency reactive compensation either completely used or insufficient. The target buses for the analysed remedial actions are selected using active and reactive power injection sensitivity factors, corresponding to critical operating constraints (identified in constraint rationalization phase). The RASIF is validated through both static and dynamic simulations to check its ability to satisfy all relevant static and dynamic security constraints during and after the transition from pre-contingency to post-contingency states.

Research Scope: The scope of this thesis falls under the intersection of power system computation and optimization, and operations research. It analyses the overstressed operating conditions in a power system with relevant mathematical models; and develops a computational framework to improve the decision-making capability of energy control centres to mitigate the overstressed operating conditions. Although the work is mainly focussed on transmission networks, the developed approaches could be easily applicable to distribution networks with minor modifications.

1.6 Outline of the Thesis

The thesis is organized into seven chapters as follows.

Chapter 1: This introductory chapter gives a general overview of the thesis. It discusses the motivation and objectives followed by contributions of the thesis.

Chapter 2: This chapter provides an introduction and theoretical background to security constraint management.

Chapter 3: Presents a mathematical and analytical formulations of security constraint management and then discusses working principles, merits, and demerits of various solution algorithms.

Chapter-4: Prepares and validates a list of feasible and infeasible SCM cases for several standard test networks. These cases will be used in later chapters to demonstrate the applicability of the proposed approaches.

Chapter 5: Presents an infeasibility diagnosis and resolution framework to identify the minimum intractable subsystem of constraints (MISC) and resolve the infeasibility in infeasible SCM formulations by either penalizing and relaxing MISC.

Chapter 6: Presents a metaheuristic framework for identifying the critical operational security constraints during the overstressed system operating conditions because of which a feasible dispatch cannot be realized. The constraint rationalization is carried out by considering the different priorities of the operator.

Chapter 7: Using the results from the constraint rationalization framework and injection sensitivity factors, this chapter presents a novel remedial action framework. Five distinctive types of remedial actions are analysed here. Full time domain (system dynamics) simulation with the remedial actions is also presented, to check the satisfiability of dynamic security constraints during the transition from pre- to post-contingency states.

Chapter 8: Discuss the conclusions and further directions (and implications) of the research presented in the thesis.

Chapter 2

Overview of Security Constraint Management Methodologies

This chapter provides an introduction and theoretical background to security constraint management.

2.1. Introduction

Arguably, the secure operation of modern electricity networks has now become an even more important and critical issue than ever before, which is mainly due to the new challenges faced by market and system operators in terms of increased penetration of renewable generation, market re-regulation and limited investments in system (transmission and distribution network) capacity enhancement. In particular, market re-regulation and reduced capacity investments require the system-operators to operate their networks closer to the operational security limits, in order to maximize the revenues while utilising available system assets. On the other hand, increased penetration of inverter-interfaced renewable generation effectively makes networks more vulnerable to even small disturbances, due to reduced system inertia, damping and fault levels.

Security of an interconnected electricity network can be defined as an ability to survive imminent disturbances (e.g. a contingency) without interrupting the customer service (i.e. disconnection of load) [18]-[19]. When a contingency happens, the power flows are re-routed, based on the physical/electrical characteristics of the re-configured network. While a pre-contingency network can enable the exchange of these power flows between the generation and demand nodes without violating operational security limits of any of the transmission asset, the post-contingency network may, or may not be able to exchange the re-routed power flows without violating some operational security limits.

Once the network operates beyond operational security limits, system security will be degraded. As these security limits influence system security and constrain the power flows, the situation representing the violation of a security limit can be considered as a "security-constraint" on electricity transmission. System operators should ensure (to the highest possible extent) that these security limits are always respected for every dispatch scheme. The prolonged operation beyond security limits may lead to cascaded tripping of components and blackout. The prompt and adequate management of these security constraints is equally important for a fair operation of competitive electricity markets, as well as for maintaining network integrity and security [20]. The following sections provide a detailed discussion and literature review of security constraint management.

2.2. Definition and Classification of Transmission Constraints

Although the outcome of a transmission constraint is the same for all networks, different ISOs employ slightly varied definitions of a transmission constraint. Some of the definitions are provided below.

A transmission constraint is defined as any limit on the ability of the national electricity transmission system, or any part of it, to transmit the power supplied onto the national electricity transmission system to the location where the demand for that power is situated (National Grid, UK) [21].

A transmission constraint is defined as occurring: 'where the transmission system is unable to transmit the power supplied onto the transmission system to the location where the demand for that power is situated (Ofgem, UK) [22].

A transmission constraint is any limit on the ability of the transmission, or any part of it, to transmit power to a location which demands it (ELEXON, UK) [23].

A transmission constraint is a constraint on the transmission network between the subsystems or between areas within a subsystem (ENTOSE, Europe) [24].

A transmission constraint is a local limitation in the transmission capacity of the grid (Transpower, New Zeeland) [25].

A transmission constraint is a physical or operational limitation on the ability of a line or piece of equipment, set to limit power flows to a safe level (DOE, USA) [26].

A transmission constraint is a limitation on the transmission network's capability to deliver electrical power, which prevents one or more market generators from generation at any desired output, up to their maximum capacity (AEMO, Australia) [27].

Given the above definitions, this thesis uses following definition: A transmission constraint between two nodes in the electricity network is defined as a limit on power exchanges between those nodes.

Depending on the generation and demand patterns, and occurrences of outages in the system, constraints may arise and disappear in real-time [28]. From grid operations viewpoint, transmission constraints are activated by the violation of two types of operational security limits [28]-[30]: steady-state security and dynamic security limits (Table *2.1*). These limits are called security limits, because their violation imposes a constraint on electricity transmission and system security depends on the satisfiability or non-satisfiability of these limits. A security limit, unless violated, cannot impose a constraint on electricity transmission in the network. The severity of a violated constraint generally depends on the amount of violation, location and consequence of the constraint, existence of other constraints, actual demand-generation pattern, and availability of the control and reserve resources.

Steady state security limits are the operating limits that must be satisfied during the steady-state operating conditions and are generally related to pre-disturbance state and post-disturbance state in which all transients and dynamics during the transition have ended. Steady-state security constraints become active when there is a violation of steady-state security limits. Violated steady-state security limits can constrain the electricity transfer among different nodes during the steady-state operating conditions. Thermal limits relate to the thermal capacity of a transmission branch (e.g. transmission line, transformer, etc), ensuring that steady-state power flow through every branch is below its thermal rating. Operation beyond the thermal rating may trigger the protection and trip the corresponding equipment from the system. Similarly, steady-state voltage at each network node should be in the allowed or acceptable voltage margin, because consumers' equipment, as well as utility equipment, may operate inefficiently, or not operate at all (e.g. electromagnetic compatibility limits would be violated) if voltages are outside this acceptable range.

Dynamic security limits are the limits that must be satisfied during the system transition between the two successive and different steady-state conditions. The transition involves the occurrence of a disturbance or large change in the system and subsequent application of some corrective control actions. System can transfer to a different steady-state safely if and only if the voltage and angle stability limits are fulfilled during the transition; otherwise, the system could end up in another disturbed state, which could potentially lead to a disconnection of a part of the system, or complete system collapse.

Table 2.1 Classification of security limits

Steady State Security Limits	**Dynamic Security Limits**
Branch thermal limits	Angle stability limits
Bus voltage limits	Voltage stability limits

2.3. Origins of Constraint Violations

Typically, system constraints are imposed by the violation of security limits, and there are two general situations in which constraints might occur. First, demand in an area cannot be offset by the localized generation and at the same time import into that area is limited by the capacity of importing circuits. Second, generation in an area cannot be offset by the localized demand and at the same time export out of that area is limited by the capacity of exporting circuits.

In modern electricity networks, there exist several reasons because of which security limits are frequently getting violated. Some of these reasons are mentioned below.

Direction of generation to load: Most of the transmission and distribution circuits in the today's power systems are designed and built back in the 20th century, according to the original power flows of that time [31]. The direction of generation capacity (i.e. installation) was planned to follow the direction of load growth [31]. However, generation in modern power systems changed its direction to load because of which the existing circuits are unable to carry the modified power flows, especially during peak-load and disturbance conditions. This further results in underutilization of some circuits and overloading and frequent tripping of some other circuits as well as bus voltage violations.

Occurrence of contingencies: Although utilities implement best preventive actions to avoid the occurrence of contingencies, contingencies do happen in power systems. While some outages are planned for maintenance activities, many of the outages are unplanned and unexpected. Contingencies are so far considered as the result of component and system faults, but, from cyber security viewpoint, they can be initiated irrespective of faults by cyber intruders [32].

Penetration of power electronic interfaced renewable generation: Modern power systems feature ever increasing penetration of power electronic interfaced renewable generation both at transmission and distribution levels. While this helps in meeting the requirements for sustainable energy supply, it significantly reduces system inertia, damping and fault levels, and increases the generation uncertainty. This makes modern electricity networks more vulnerable to even small disturbances which may lead to equipment contingencies (e.g. tripping of inverter-interfaced generation) and hence transmission congestion [33].

Re-regulated Markets [34]-[36]: Until the end of the 20th century, power systems were mainly regulated by government entities. Governments took the responsibility for maintaining quality, security, and reliability of electricity service by making needed investments and performing all the necessary functions. Nowadays, however, power systems and electricity markets are privatised for the reasons of more efficient and optimal use of system assets. In a re-regulated environment, private investors can take independent decision according to their own assessments rather than those of the government re-regulated bodies. System operators are forced to operate their networks near to, or at its physical security limits, in order to increase their profit margin. This results in the highly stressed and overstressed power systems, in which a small disturbance can result in unavailability of many system components and lead to emergency operating conditions (and existence of many security constraints or impose many security constraints).

Limited and delayed investment in transmission expansion: While there is a significant increase in demand and renewable generation penetration in recent years, transmission circuits have not been upgraded accordingly, or there are significant delays in upgrading and re-enforcing due to environmental restrictions and limited investments [37]-[40]. Insufficient funding, frequently changing regulatory frameworks with reduced incentives, and increased financial risk are some of many factors limiting the investments in transmission expansion [38]-[40].

As the cost of managing possible constraints violations in some cases is lower than further investment in the transmission network, operating the system closer to some of security limits/constraints might be an economically efficient option.

2.4. Consequences of Constraint Violations

Violated constraints must be resolved as and when they arise, as otherwise there will be suboptimal power flows across interties, equipment damages, supply interruptions, and even blackouts. For example, a line outage due to a fault can result in overloading of other lines, which may be eventually tripped. Other lines are then overloaded, and a cascade of disconnections might be set in motion [41].

Independent system operators (ISO) or Transmission system operator (TSOs) procure various ancillary services, in order to manage the constraints during all system operating conditions and to control/balance power flows from the generation points to the load points. ISO/TSOs pay millions of dollars as constraint payments to ancillary service providers every year. For example, National Grid (UK) paid around £340M pounds as constraint management payments [21]. Hence, constraint management at lower cost is particularly important and any progress in this area could result in significant savings to network operators, which will further result in reduced energy prices to consumers.

2.5. Security Constraints versus Operating Conditions

Strictly speaking, every disturbance or a change in control action shifts the operating point from one location (i.e. present operating point) to another (i.e. the future operating point). The shift in the operating point may be small or large, depending on the severity of the disturbance. For example, a minor change in demand typically causes a small shift, while tripping of the major load or generation typically moves the operating point farther away from the previous location.

If the future operating point meets a predefined (technical and/or economic) performance criteria, there is no need to take any preventive or corrective actions. If not, the operator should implement relevant preventive/corrective actions in adequate or available time for their activation and realisation, to bring the system back to the previous operating point, or safely transit the system to another acceptable, i.e. secure operating point. However, until and unless the response of the network is known at numerous operating points, or states in a multi-dimensional operating space, system planners cannot devise proper guidelines and system operators cannot implement required corrective and preventive actions in a prompt and confident manner. Therefore, it would be important to decompose multi-dimensional operating space into a set of operating regions, so-called classification of operating points.

2.5.1. Classification of Power System Operating States

The classification of system operating points, or system states, plays a key role in power system planning and operation, as it helps planning engineers and operators in designing and implementing proper control strategies for several expected, unexpected and undesired operating points. The framework for classifying operating points is initially proposed in [42] and then extended in [43]. As references [42]-[44] suggest, all possible operating points can be classified into five broad categories, based on the degree to which the system adequacy and security were satisfied. While the adequacy is expressed through power balance constraints (also called equality or *adequacy constraints*), security is expressed through operational security limits (also called inequality or *security constraints*).

A. Normal State (N)

At the normal operating point, both adequacy and security constraints are satisfied, indicating that generation can meet the demand without violating any operational security limit of any asset (i.e. none of the security constraint is active). In the normal operating region, consisting of normal operating points, the system is considered to have sufficient level of security reserves to withstand every single contingency with or without the implementation of any manual or automatic corrective action. Hence this operating state is also considered as a “secure” state.

B. Alert state (A)

In alert operating state, both adequacy and security constraints are still satisfied, but the existing reserve margins are such that some disturbance (if it takes place) could result in a violation of at least one security constraint. Alert state is an indication that the system is vulnerable to failures and requires implementation of necessary preventive actions to avoid security constraint violations. The system enters the alert operating region whenever the security reserves fall below some threshold value, or the probability of occurrence of disturbance with a strong negative impact increase.

C. Emergency state (E)

If a sufficiently severe disturbance takes place before (or despite of) implemented preventive actions, the system enters the emergency operating region. In this region, adequacy constraints are still satisfied, but at least one security constraint is violated. For example, some transmission lines might be operating beyond their allowed/emergency rating and some bus voltages are above/below their threshold voltage limits. However, the system could be still intact, at least for some time. In this lead time, operators must devise proper (emergency) corrective controls (so-called remedial actions) to prevent network breakdown and equipment damage. Emergency corrective control actions include load shedding, active and reactive reserves switching, network reconfiguration, generator re-dispatching, activation of demand-side manageable loads, etc.

D. Extreme Emergency state (ExE)

If emergency corrective actions are not implemented in time or are ineffective, or a severe subsequent disturbance takes place, the protection systems will start to disconnect network components due to excessive stress or moving of operating points outside of allowed and safe ranges. This operating region is considered as the extreme emergency operating region. In this region, both adequacy and security constraints are violated, and the system is no longer intact, as protection has disconnected some loads and/or system components. Some system components will be either disconnected by protection or will be working beyond their emergency rating. Both situations typically result in a loss of major portions of the network supplying larger amounts of total system load. At this stage, further emergency corrective control actions should be directed toward preserving the system from the total collapse.

E. Restorative state (R)

In emergency state, the equality and inequality constraints are violated, while the system is breaking up into independent parts, resulting in the formation of “islands” that may or may not be energized. Once the collapse had been halted, if there were any remaining components working within rated capability, or if some equipment had been successfully restarted following the prevention of the system collapse, system could enter the restorative operating region. The corresponding control actions (i.e. *restorative controls*) in this region are aimed to pick up all or most of the lost load and to reconnect islanded parts. Following implementation of restorative controls, system should transit to alert, or to normal operating point, depending on the circumstances and considered time period.

Some researchers divided the emergency conditions into further types. In [45], emergency states are divided into steady state emergency and dynamic emergency (instability) states. In steady state emergency state, steady state security constraints are violated, but the system can still maintain the stability. In the dynamic emergency state, dynamic security constraints are violated, and the system cannot maintain the stability. Accordingly, the steady-state emergency condition may be tolerated for a reasonably long period, allowing the emergency corrective actions to be taken. The dynamic emergency condition takes place in a short period of time and unless a proper fast corrective action is taken, the system ends up in a restorative state [46].

In [47], emergency states are also divided into steady state and dynamic emergency states, but definitions are slightly different. The system is in a steady state emergency when it cannot serve all the load, or when it can serve all the load, but some security constraints are violated. The system is in a dynamic emergency state when the synchronous operation is threatened, or frequency is decreasing due to insufficient generation to match the load.

Classification of emergency conditions into correctable emergency state and non-correctible emergency state is given in [48]. The correctable emergency state is the one at which all the load is supplied but some operating limits or security constraints are violated. However, these violations can be corrected by appropriate corrective controls without loss of load. The non-correctable emergency state is the one at which all the load is supplied, and some operating limits are violated. But these violations cannot be corrected without loss of load.

2.5.2. Stressed and Overstressed Operating Conditions

The existing operating point classifications have neither defined the stressed and overstressed operating conditions, nor they say where these conditions fall within the existing framework. Although some aspects of the analysis in existing literature concentrated on “stressed systems”, e.g. [49]-[51], there was neither a concrete definition of a ‘stressed system’, nor a method for quantifying the level of stress [52]. Different people/organizations have differently perceived stressed and overstressed operating conditions [51]-[64]. Moreover, the concept of stressed and overstressed events is seen differently by industry and academia.

In the majority of the existing literature, [51]-[54], it is said that the system is stressed when it is operating near to its operational limits, but how close to the limit is considered as “*close”* has not been discussed. In some other literature, the operating conditions that lead to voltage instability are considered as stressed conditions [55]-[56]. But this approach has mostly concentrated on voltage security, rather than on both thermal and voltage security. Heavy loading (e.g. near to max demand) conditions are considered as stressed and even overstressed conditions in some other works [57]-[60], although a system with transmission capacity higher than the maximum demand should supply this maximum demand with no constraint violation. National Grid (UK) consider that the system is stressed when the capacity margins are less than 20%, or when the demand control instruction is inevitable; the system is highly stressed when the capacity margins are less than 10% [61]-[62]. According to PJM [63], the operating conditions where the ancillary services are insufficient, or the prices are very high to maintain the network balance are considered as stressed operating conditions. According to EPRI [64], the operating conditions at which the intervention of remedial actions is necessary to maintain the energy balance are considered as stressed operating conditions.

The previous definitions or assumptions have not properly linked the stressed and overstressed operating conditions into existing operating point classification framework and have not provided a methodology to diagnose them. Traditional security constraint management procedures are not associated with tools that can detect and diagnose the stressed and overstressed operating conditions, as confirmed by the number of blackouts [51]. Hence, there is a need for mathematical approaches and tools to detect and diagnose these stressed and overstressed conditions, as the system is more vulnerable to even small disturbances and the probability of cascaded outages is significantly higher during the stressed and particularly overstressed operating conditions. The required approaches must be simple, intuitive, practical, and easy to visualize, so that operators can use it and respond quickly by issuing proper control actions.

This thesis proposes such a simple methodology based on the status of steady state security constraint violations. The proposed approach considers steady state security limits as stress indicators (Table *2.2*) and divides the operating region into unstressed, stressed, and overstressed regions. A description on how to relate these definitions to existing operating point classification framework is also provided (Figure *2.1*).

Table 2.2 System Stress Indicators

Stress Indicator	**Type of Stress**	**Main Causes**	**Possible Consequences**
Line Loading	Thermal	Local flows of active powers	Angle and frequency instability
Bus Voltage	Electrical	Local flows of reactive powers	Voltage collapse or voltage instability

Unstressed system: is the system at an operating point where all steady state security constraints are satisfied. Additionally, the differences between their present values and maximum and minimum allowed values are sufficiently large, so there will be no further security constraint violations for any credible contingency related to that operating point. This could be also denoted as the “normal” system operation state.

Stressed system: is the system operating at a point where at least one of the security constraints is violated and several other security constraints are close to their allowed limit values, but the network can still maintain the energy balance. For example, the loading of a line is above its maximum limit, but the system can be brought back to the normal unstressed operating point by adjusting (non-emergency) corrective controls to reduce line loading without violating any further constraint. This could be denoted as the "emergency" operating state of the system.

Overstressed system: is the system at an operating point at which at least one of the violated security constraints is critical. At this operating point, the system energy balance is lost, and system cannot be brought back to the normal state with the existing corrective controls. The system can only be brought back with prompt activation of emergency controls. This could be denoted as transitional state between emergency and extreme emergency state, where prolonged operation at over stressed condition leads to extreme emergency state.

Network operators can employ the proposed classification of system stress to identify the stressed and overstressed operating conditions as well as to implement the relevant mitigative actions (Figure *2.1*).

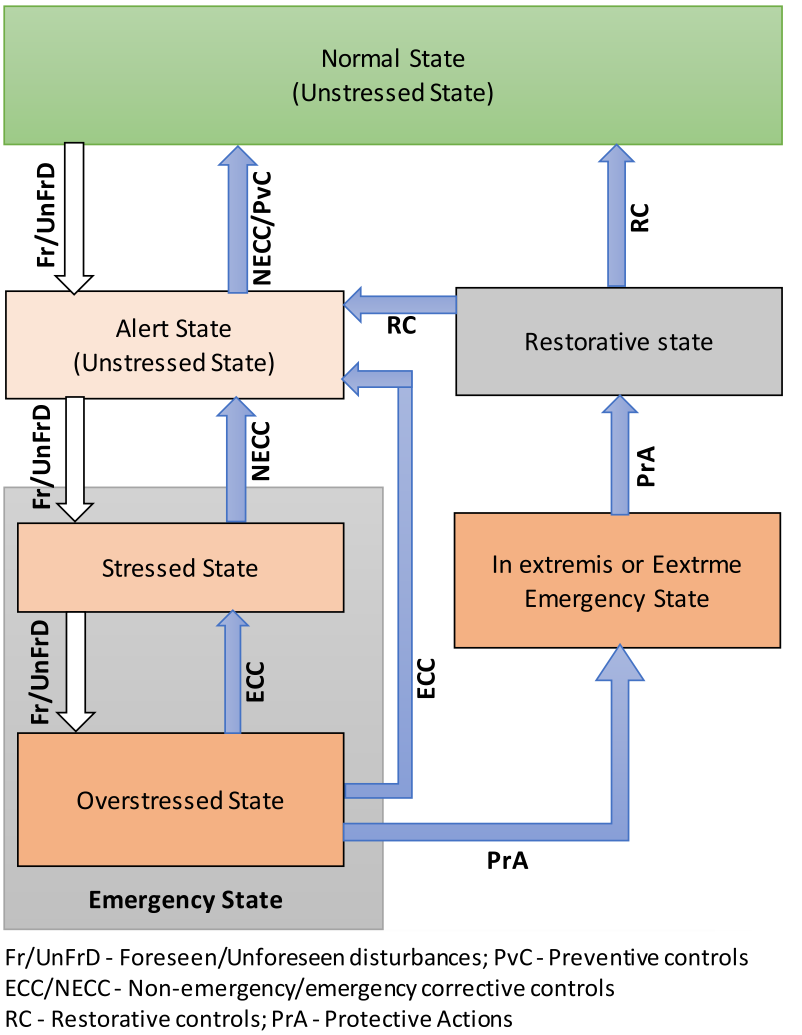


Figure 2.1 System Operating States with Possible Transitions

2.6. Security Assessment

Security assessment is one of the most important tasks in power system planning and operation. Following a disturbance, different components will respond differently, depending on location and time of occurrence of disturbance, which will shift the system to a new operating point. At post-disturbance operating point, system may or may not violate the steady state security limits (branch thermal limits and bus voltage limits) and dynamic security limits (voltage and angle stability limits), while transferring from present to future steady state operating point.

The purpose of the security assessment is to check whether the present operating point is secure or not, by estimating the degree to which the static and dynamic security limits are satisfied and devise proper preventive and corrective control actions, if necessary. This is achieved by analysing/simulating all credible contingencies at present operating point and checking the satisfiability of security limits at the corresponding post-contingency operating points [65].

Static security assessment and dynamic security assessment are two main subfields of security assessment [66]. While static security assessment evaluates the satisfiability of steady state security limits, dynamic security assessment evaluates the satisfiability of dynamic security limits during the transition [67].

In general, system security assessment is divided into three parts: a) system monitoring, b) contingency analysis, and c) security actions [68].

2.6.1 System Monitoring

System monitoring provides the network operators with relevant and up to date information on the system. Usually, SCADA system captures the component status information (e.g. on/off status of circuit breakers, switches, positions of OLTC, etc.), as well as other relevant information (i.e. generation, consumption, voltages, etc). This information is then used for the state estimation, together with network topology processor, in order to produce the “best estimate” (in a statistical sense) of the current system operating point [68].

2.6.2 Contingency Analysis

Contingency analysis is further classified into three categories: contingency definition, screening, and evaluation. Contingency definition prepares the list of all credible contingencies for various network configurations and operating conditions. The credible contingencies are the contingencies with a high probability of occurrence. Typically, utility companies provide the component-failure rates. While the contingency screening filters critical contingencies from all credible contingencies, contingency evaluation performs detailed assessment of these critical contingencies, using full ac-power flow algorithms and time domain simulations.

2.6.3 Security Controls

Although network-operators try to run the network always within the normal and secure operating region, unplanned and unexpected disturbances do happen, and system may enter unsecure region of operation. Network operators, in these situations, should take control actions, so called *security controls*, to reinstate the security of the system. Traditionally, security controls have been divided into two main categories: preventive and corrective security controls [66]. While preventive controls are implemented before the occurrence of the disturbances to prepare the system to face these disturbances in a satisfactory way, corrective controls are implemented after the occurrence of disturbances, to both minimize the consequences and return the system back to secure operating region [70].

Corrective controls can be divided into non-emergency, emergency, and restorative corrective controls. The objective of the non-emergency corrective controls (NECC) is to return the system to the normal operating region following a disturbance or contingency. The objective of the emergency corrective controls (ECC) is to return the system to normal or at least alert operating region from emergency conditions, while minimizing the impact of emergencies. Emergency control actions are usually automatic but are sometimes also operator initiated. The objective of the restorative controls is to restore supply to all disconnected loads by re-connecting all disconnected islands and to bring the system back to normal, or at least alert operating condition.

Non-emergency corrective controls generally include: generation rescheduling, network reconfiguration, reactive compensation, etc; emergency corrective controls include: direct and indirect load shedding, generation shedding, emergency generation connection, shunt capacitor or reactive switching, network splitting, etc [66], [70].

2.7. Security Constraint Management (SCM)

The mathematical procedure to check the degree of satisfiability of security limits is known as security assessment, or security analysis, and is further divided into static and dynamic security assessment. Static security assessment checks the satisfiability of only steady state security limits, while dynamic security assessment checks the satisfiability only dynamic security limits.

Steady state security analysis is performed for a specific the operating point, while the dynamic security analysis is performed during the transition between two operating points. If all the steady state security constraints are satisfied at an operating point, the operating point is considered as “steady state secure”. If all the dynamic security constraints are satisfied during the transition from the present operating point to another point, the transition between these two operating points is “dynamic secure”. A system is secure if steady-state security constraints are fulfilled both at pre- and post-disturbance operating points, and if dynamic security constraints are fulfilled during the transition to post-disturbance operating point.

Neglecting small load and generation variations, a static secure system, will continue to stay at same steady-state-secure operating point as long as no disturbance that can push the system to another operating point takes place. There is no need to check the satisfiability of dynamic security constraints, unless there is a considerable shift in the operating point. While all transitions are possible from mathematical analysis viewpoint, some transitions are not possible on the physical system (Table *2.3*). For example, a dynamic insecure transition never leads to a static-secure operating point, it leads to much more severe static-insecure operating point or blackout.

From the point of real-time or near-real-time operation, the management/resolution of the security constraints are denoted as security constraint management, or transmission security constraint management, or simply transmission constraint management. ISO or TSOs procure various ancillary services to manage the constraints during all conditions and balance the load.

Table 2.3 Possible Transitions of System States

Pre-disturbance OP	Transition	Post-disturbance OP	Possibility	Notes
Static secure (N)	Dynamic secure	Static secure	Yes	N-1 secure system may achieve this. (Default control is enough, or no control is needed)
Static secure (N or A)	Dynamic secure	Static insecure	Yes	Default control is not enough. Applied control is not enough State change happens
Static secure (N or A)	Dynamic insecure	Static secure	No	This transition is not possible in a real system because steady state cannot be reached if transition failed
Static secure (N or A)	Dynamic insecure	Static insecure	Yes	System reaches insecure state. State change happens. May lead to Emergency state
Static insecure (E or ExE)	Dynamic secure	Static secure	Yes	Possible with corrective control. Control Successful
Static insecure (E or ExE)	Dynamic secure	Static insecure	Yes	Possible with corrective control but control failed. System reaches insecure state. State change happens. May lead to Emergency state.
Static insecure (E or ExE)	Dynamic insecure	Static secure	No	This transition is not possible in real system, because steady state cannot be reached if transition failed
Static insecure (E or ExE)	Dynamic insecure	Static insecure	Yes	Possible with corrective control but control failed. System reaches insecure state. State change happens. May lead to Emergency state.

OP-operating point; N,A, E and ExE – Normal, alert, emergency, and extreme emergency states

In the first instance, before any constraint becomes active, operators always try to implement preventive actions to avoid the occurrence of the constraints. But, as mentioned, some unplanned/non-credible disturbances might occur suddenly, leaving no time for the operator to implement preventive actions and some constraints become active. Operators are in-charge to control these situations, as they can use any sort of resources within their boundary (considering their costs) to control these situations. Generally, operators will try to use the (non-emergency) corrective controls (primary, secondary, tertiary active and reactive controls) available on hand to restore the security. But there exist situations (e.g. some severe contingency events) in which the available non-emergency corrective controls are not sufficient to devise a feasible dispatch. In these cases, the operators go for more expensive emergency corrective controls (e.g. load shedding, curtailment of wind generation, corrective controls in neighbouring network operator’s area) to restore the static security through a successful transition.

The easiest solution to mitigate constraints violations is to activate all possible controls (both NECC and ECC) at all possible locations, but this solution may not be techno-economically efficient. For example, if a situation involves too many active constraints (e.g. more than 10), the corrective actions devised using this analogy will be extremely expensive. In fact, these costs down the line are imposed on consumer electricity bills. A tool which guides the operator to identify the critical active constraints out of all active constraints, and also aids operator to identify the potential solutions and potential locations (and the cost of each solution as a lookup table), would significantly improve the decision-making capability of operators. In the worst case, if no solution possible, it would help operators calculate the minimum amount of load to be disconnected to avoid the system collapse due to cascaded tripping, and blackout or instability. Moreover, such a tool will improve the confidence of operators on their decision. They can say to the market operators that they have tried all resorts, and all have failed.

2.8. Process of Constraint Management

This thesis proposes a modified security constraint management procedure to mitigate the overstressed operating conditions. While Algorithm 2.1 presents the overview of the existing constraint management procedure followed by the system operators and engineers, Algorithm 2.2 details the modified procedure proposed in the thesis. The important difference between the existing and modified procedure is the constraint rationalization.

Algorithm 2.1: Existing SCM procedure

1) Identify the violated security limits i.e. active security constraints
2) Select the available (non-emergency) corrective controls
3) Formulate SCM problem with selected controls
4) Solve SCM problem using an algorithm
5) If the problem is solved go to Step 7, else go to Step 6. If the SCM case is feasible, problem will be solvable, else unsolvable (i.e. system operating under overstressed conditions).
6) Add (emergency) corrective controls (i.e. remedial actions) and go to Step 3
7) Check the dynamic security of transition
8) If the dynamic security check passed, go to Step 10, else go to Step 9
9) Change the selected controls and then go to Step 3
10) Implement new control settings and resolve all active constraints

If the system is operating under the non-overstressed conditions, SCM problem becomes feasible and there exists a solution since non-emergency corrective controls are adequate to resolve all active security constraints. If the system is operating under overstressed operating conditions, SCM problem becomes infeasible, there exists no solution with the non-emergency corrective controls. Prolonged operation under these conditions can potentially lead to cascading outages and partial/complete blackout. The system must require the activation of emergency corrective controls to resolve the constraint violations during these overstressed conditions.

Existing constraint management procedure selects and issues the emergency corrective controls (so-called remedial actions) based on the occurrence of predefined events and the level of control is fixed. But the proposed constraint management procedure first identifies the critical constraints that are the root causes for developing overstressed operating conditions. These critical constraints, from the network viewpoint, are the most stressed assets (e.g. overloaded branches). Using the locations of these critical assets, modified procedure devises the location, type and amount of emergency control action. The detailed discussion and benefits of the modified procedure are presented with numerous examples in Chapter 5, Chapter 6 and Chapter 7.

Algorithm 2.2: Modified SCM Procedure

1) Identify the violated security limits i.e. active security constraints
2) Select the available (non-emergency) corrective controls
3) Formulate SCM problem with selected controls
4) Solve SCM problem using an algorithm
5) If the problem solved go to Step 8 else go to Step 6. If the SCM case is feasible problem will be solvable else unsolvable (i.e. system operating under overstressed conditions).
6) Activate constraint rationalization and find the critical active constraints according to operator priority
7) Using the locations of critical constraints, identify the type, amount, and location of (emergency) corrective controls and then go to Step 3.
8) Check the security of dynamic transition
9) If the dynamic security check passed go to Step 11 else go to Step 10
10) Change the configuration of selected controls and then go to Step 3
11) Implement new control settings and resolve all active constraints

2.9. Classification of SCM cases

The mathematical relevance of overstressed conditions can be observed in both static and dynamic analysis of the considered system. From steady state viewpoint, mathematical formulation of the relevant constraint management problem becomes infeasible, and the corresponding numerical algorithm either non-converge, or diverge due to ill-conditioning of underlying matrices, or inability to select proper initial values. From dynamic analysis viewpoint, the numerical integration may also become infeasible due to inability of finding feasible initial values from steady state analysis, or numerical infeasibility.

Considering the above, SCM problem formulations are divided into feasible and infeasible SCM cases in this thesis. While feasible SCM case has zero active constraints that cannot be resolved by available/modelled non-emergency corrective controls, infeasible SCM case has at least one active constraint that cannot be resolved by available non-emergency corrective controls. Hence, these cases are also called as manageable and non-manageable SCM cases in prevailing industrial terminology.

The mathematical formulation of an SCM problem is feasible if it has a solution (i.e. NECC solution) satisfying all constraints, and infeasible if it does not have any solution satisfying all equality and inequality constraints simultaneously. This judgment assumes that there is an algorithm which can find the solution (if there is one), or otherwise notify there is no solution. If the violated constraints are divided into critical and noncritical constraints, manageable SCM case always has zero number of critical constraint violations, while the non-manageable case always has a nonzero number of critical constraint violations. This situation happens during overstressed and emergency operating conditions, where either the available non-emergency corrective controls are insufficient, or the location of the available controls is not suitable for resolving all constraint violations.

2.10. Literature Review

The background literature of the thesis span across four different fields: overstressed operating conditions, infeasibility diagnosis in nonlinear OPF programs, constraint rationalization and remedial action schemes. As the thesis takes motivation from different fields, it would be difficult to provide a coherent discussion of the background literature in one place. Hence, I intentionally decided to present the detailed literature in related chapters where it appropriate. Nevertheless, the brief overview of the literature and where the detailed literature is available is explained below.

Over stressed operating conditions [49] - [64]: Although some studies focussed on stressed and overstressed power systems, there was neither a concrete definition of a ‘stressed system’, nor a method for quantifying the level of stress. The existing operating point classification framework has neither defined stressed and overstressed conditions nor it said where these conditions fall within the existing framework and how to diagnose and model these conditions. So, there is an obvious need to define as well as link these conditions to the existing operating point classification framework. With an aim to address this gap, this thesis proposed a simple methodology to define stressed and overstressed operating conditions in Section 2.5.2 and the detailed literature is also provided there itself.

Infeasibility diagnosis in nonlinear OPF programs [3-6, [10,12, 14, 17, 48, 71-89]: Although there exist methods to diagnose the infeasibility in liner OPF programs, no reliable method exists for diagnosing infeasibility in nonlinear OPF programs. Chapter 5 presents a detailed literature review of the infeasibility diagnosis in nonlinear OPF programs and proposes an infeasibility diagnosis and resolution framework (IDRF) with an aim to address the research gap in existing literature.

Constraint rationalization [28, 43, 81, 90-99]: While most of the existing literature on constraint management has focussed on resolving constraint violations through various controls, very few works focussed on identifying the critical constraints based on operator priorities (especially during overstressed operating conditions) and use the knowledge of critical constraint to devise most effective corrective actions. Chapter 6 presents a detailed literature review and proposes a constraint rationalization framework (CRF) to identify the critical constraints during overstressed conditions.

Remedial action schemes [3,4, 14, 21, 28, 51, 100-127]: Most of the previous RASs are designed based on planning analysis and they are event-driven and fixed. As the system evolves over time, these RAS may be ineffective from the technical and/or economic viewpoint. Consequently, there is an obvious need to devise response-driven driven RAS in the operations environment, using system physical models and/or real-time measurements. Chapter 7 presents a detailed literature as well as proposes a remedial action selection and implementation framework (RASIF) to devise the most effective response-driven RAS during to mitigate overstressed conditions.

2.11. Conclusions

Constraint management is one of the continuous and fundamental tasks done by system operators. Independent system operators spend millions of dollars in procuring various constraint management services to mitigate constraint violations. This chapter, based on the satisfiability of steady state security constraints, presented a simple methodology to define as well as diagnose the stressed and overstressed operating states. These definitions were made in align with the existing classification of system operating states. The main reasons for the constraint violations in modern electricity networks and the impact of constraint violations are discussed. Finally, this chapter explained that these overstressed operating conditions can be interpreted as infeasible mathematical formulations of the SCM problems.

Chapter 3

SCM Problem Formulation and Solution Algorithms

This chapter presents a mathematical and analytical formulations of security constraint management and then discusses working principles, merits, and demerits of various solution algorithms.

3.1 Introduction

The management of the steady state security constraints, involving their identification and corrective actions in case they are violated, is referred to as security constraint management (SCM) [1]. SCM remains to be one of the critical tasks performed by the engineers and network operators during the system planning and operations. In general, SCM is formulated as a nonlinear constrained optimization problem and can be solved by either conventional (gradient-based) approaches, or non-conventional (metaheuristic) approaches [7]. The rest of this chapter explains the detailed modelling of the SCM problem and the relevant solution algorithms employed in this thesis.

The rest of the chapter is organized as follows: Section 3.2 presents the problem formulation. Section 3.3 provides key insights into the problem formulation. An overview of solution algorithms is discussed in Section 3.4 and detailed discussion of implemented solution algorithms is presented in Section 3.5. Section 3.6 discusses the employed penalty functions in the thesis, and Section 3.7 concludes the chapter.

3.2 SCM Problem Formulation

The objective of an SCM problem is to find the optimal control solution that resolve all constraint violations while minimizing the cost of achieving that solution. SCM can be mathematically formulated as a nonlinear, nonconvex and constrained optimization problem, (3.1) - (3.3). It should be noted that the SCM mathematical formulation is similar to Optimal Power Flow (OPF) formulation in power systems. OPF is one of the fundamental mathematical formulations in power system engineering and most of the network-level planning and operational problems can be analysed using OPF formulation, and SCM is no exception to that.

$$min. \quad f(x_0, u_0) \tag{3.1}$$

$$s.t. \quad g(x_c, u_0) = 0 \tag{3.2}$$

$$h(x_c, u_0\ ) \leq 0, c \in C = \{0,1,2, \dots N_c\} \tag{3.3}$$

where: *x*, *u*: state and control variables, *c*: contingency index (zero for base case), *C*: set of credible contingencies, *f*: objective function, *g*: equality constraints, *h*: inequality constraints.

The main difference between general OPF formulation and SCM formulation is the objective function (*f*) and inequality constraints (*h*) of interest. General OPF formulation analyses the network with a range of objective functions, e.g. fuel cost, (3.4), emission, (3.5), loss (3.6), etc, which may or may not include transmission security constraints (static and dynamic security limits). But, SCM formulation focuses on finding a feasible and (if possible) optimal corrective control solution at optimized control priority or objective (e.g. cost of feasible control solution, (3.4), available lead-time for next contingency, disconnected load, etc). Chapter-6 provides a detailed discussion on employed control priorities in this thesis.

$$F_T = \sum_{i=1}^{NG} [a_i P_{Gi}^2 + b_i P_{Gi} + c_i] \quad \$/h \tag{3.4}$$

$$E_T = \sum_{i=1}^{NG} [d_i P_{Gi}^2 + e_i P_{Gi} + f_i] \quad CO2\_ton/h \tag{3.5}$$

$$P_{loss} = \frac{1}{2} \sum_{i=1}^{NB} \sum_{j=1}^{NB} G(i,j) \left[V_i^2 + V_j^2 - 2V_i V_j \cos\left(\theta_i - \theta_j\right)\right] \quad MW \tag{3.6}$$

Equality constraints, (3.2), are represented by the nodal power balance equations, (3.7)-(3.8). Inequality constraints, (3.3), represent equipment operating limits: generator real and reactive power limits, (3.9)-(3.10), transformer tap setting limits, (3.11), and branch thermal rating limits, (3.12), as well as bus voltage limits, (3.13).

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \cos\left(\theta_i - \theta_j\right) + B_{ij} \sin\left(\theta_i - \theta_j\right)\right] = 0 \tag{3.7}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \sin(\theta_i - \theta_j) + B_{ij} \cos(\theta_i - \theta_j)\right] = 0 \tag{3.8}$$

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max}, i = 1, 2, \dots NG \tag{3.9}$$

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}, i = 1, 2, \dots NG \tag{3.10}$$

$$T_i^{min} \le T_i \le T_i^{max}, i = 1, 2, \dots NT \tag{3.11}$$

$$S_{li} \le S_{li}^{max}, i = 1, 2, \dots NL \tag{3.12}$$

$$V_i^{min} \le V_i \le V_i^{max}, i = 1, 2, \dots NB \tag{3.13}$$

Where: P_{Gi}, Q_{Gi} – real and reactive power output of generator i, P_{Di}, Q_{Di} – real and reactive demand at bus i, V_i, θ_i – Voltage magnitude and phase angle at bus i, F_T, E_T – total fuel cost and emission, P_{loss} – total active power loss in the system, a_i, b_i, c_i – fuel cost coefficients of generating unit i, d_i, e_i, f_i - Emission coefficients of generating unit i, N_B, N_G, N_L- Number of buses, generators and branches, G_{ij}, B_{ij} – conductance and admittance of a line connecting buses i and j.

3.3 Insights into the Problem Formulation

This section explains some fundamental definitions and concepts of optimization that are important to understand the methodologies proposed in this thesis.

3.3.1 Feasible and Infeasible Search Space

A feasible search space is the set of all possible (i.e. physically feasible) operating points that satisfy all stipulated constraints. Every point in the feasible search space could be a solution to the problem, and the optimization algorithms explore this feasible search space to find the most optimal point. If the constraints are contradictory (e.g. satisfaction of one constraint requires violation of other constraint), there are no points that satisfy all the constraints and thus the feasible region is the null set. If the feasible region is a null set, then the search space is said to be infeasible [17, 128, 129].

3.3.2 Feasible and Infeasible Problem Formulation

SCM problem formulation is said to be feasible if there exists a solution which satisfies all equality and inequality constraints simultaneously and infeasible if there exists no such solution. This judgment assumes that there is an algorithm which can find a feasible solution (if there is one), or else report infeasibility (if there is no solution).

In general, an optimization model can become infeasible due to following three reasons:

Infeasibility due to formulation or data errors: Modeller or analyst mistakes (e.g. misplacement of upper and lower limits of a specific constraint), or corrupted data (e.g. data received from SCADA system may be wrong because of bad data or corrupted by cyber attacker) can lead to infeasible formulation [4, 17]. In this case, optimization algorithm either throws an error due to numerical failure (e.g. calculation of a square root of a negative value), or reports infeasibility. This infeasibility can be denoted as "*data infeasibility*" and it is the most common infeasibility in SCM formulations. Most of the commercial optimization solvers, as well as power system optimization software have embedded techniques to detect and resolve data infeasibility.

Infeasibility due to scaling issues: Sometimes, even though there are no modelling and data mistakes, the algorithm may still report infeasibility due to scaling issues. For example, bad scaling of Lagrangian and penalty multipliers for equality and inequality constraints may lead to the ill-conditioning of involved matrices (e.g. Jacobian). When this happens, matrix inversion algorithms may fail, and optimization algorithms halt the progress, as the corrections required to update the search variables for the next iteration cannot be calculated. This infeasibility is denoted as "*scaling infeasibility"*. Scaling infeasibility is not common, because most of the commercial solvers implement preconditioning of variables to prevent scaling issues.

Infeasibility due to infeasible search space: If the search space becomes infeasible, the algorithm reports infeasibility, as there is no solution which satisfies all constraints. This infeasibility is denoted as "*true infeasibility*" because this is the only type of infeasibility that represents the actual infeasibility in the problem formulation. Accordingly, data and scaling infeasibilities are denoted as "*false infeasibilities",* as these does not represent the actual infeasibility. In case of data and scaling issues, there exists a solution, but optimization algorithms are unable to find that solution because of the data errors and/or scaling issues.

In case of true infeasibility, the gradients of the active inequality constraints and the gradients of the equality constraints become linearly dependent. That is why the Newton matrix (or equivalent that involves solving KKT conditions via gradient based equation solvers) becomes singular or has extremely high condition number. When this happens, matrix inversion algorithms may fail and hence optimization algorithms had to halt the progress, as they cannot calculate the corrections to update the search variables for the next iteration.

In general, true infeasibility happens when the required resources are greater than the available resources, or when there are conflicting requirements. For example, an SCM solution algorithm will report a true infeasibility when the available controls are insufficient to devise a feasible dispatch that respects all security constraints [4]. This situation typically happens during stressed and overstressed operating conditions, when available controls are exhausted, and some constraints cannot be satisfied [4, 130]. As mentioned in Chapter 2, modern electricity networks are frequently operated under stressed and sometimes under overstressed operating conditions, in order to meet the market requirements and to integrate more renewable energy.

Moreover, the increased penetration of renewable energy can change the direction and levels of power flows across several branches, and the existing networks may not be able to carry these changed power flows. Hence, the increased levels of renewable generation (with no further investment in transmission) can potentially lead to infeasible power flows. This thesis focuses on true infeasible SCM formulations related to the occurrence of overstressed operating conditions.

3.3.3 Infeasibility Detection and Certification

It is necessary to detect and certify/confirm infeasibility, to avoid spending large computational times on trying to find a solution which does not exist. If the infeasibility is confirmed, an optimization algorithm can concentrate on feasibility, rather than optimality. It is quite complex to prove infeasibility in nonlinear optimization problems, compared to linear optimization problems. This becomes much severe when the problem is nonconvex, and the constraints are nonlinear functions [17]. Metaheuristic algorithms can be used to solve find a reasonably good solution to these kinds of problems although they may not provide (global) optimal solution.

Infeasibility diagnosis in nonlinear optimization is still an immature research topic and more reliable and accurate methods are needed to find and decide infeasibility [131]. While there exist reliable certificates (e.g. Farkas lemma) to prove global infeasibility in linear optimization problems, a very few certificates exist to prove even local infeasibility for nonlinear optimization problems. Moreover, these certificates are applicable to nonlinear problems with specific structures (e.g. convex problem). A more detailed information on infeasibility certificates for nonlinear optimization problems can be found in [132]-[135].

As mentioned earlier, infeasibility conditions/status can be observed by checking the linear independence of gradients of active inequality constraints against the gradients of equality constraints [82, 89, 136], or by checking the condition number of Newton matrix. If the condition number of Newton matrix is close to singular, it can be confirmed that the problem is infeasible. Moreover, use of more than one solver can help, as it is unlikely that two or more solvers will make a wrong judgement on infeasibility [137].

It should be noted that the aim of this thesis is not to develop any infeasibility certificates. Hence, in this thesis the proof of the infeasibility of the considered SCM formulations is obtained: a) by checking the condition number of Newton matrix, b) by solving SCM problems with different open-source and commercial solvers. This will be discussed in detail in Chapters 4 and 5.

3.3.4 Infeasibility Diagnosis and Localization

Given an infeasible model, it is very important to localize the infeasibility in order to make engineering decisions with reduced risk and cost. In the case of infeasible SCM problems, it would be useful to know the locations of underlying constraints, so that appropriate corrective actions may be taken. In general, an optimization model for power system analysis will become infeasible due to only a small set of non-satisfiable constraints [100]. Once these constraints are identified, infeasibility can be resolved by either relaxing them, or by placing (planning stage) or activating (operational stage) additional resources at the effective locations.

Hence, the infeasibility diagnosis of SCM model can be expressed as following question: what is the smallest set of security constraints to be resolved, so that the remaining constraints constitute a feasible set? In that context, this thesis adopts the concept of the minimum intractable subsystem of constraints (MISC, defined below) from optimization theory and implement it to infeasible SCM problems. From the point of infeasible SCM modelling, MISC is redefined as the critical security constraint subsystem, or simply critical constraint subsystem (CCS).

Minimum Intractable Subsystem of Constraints (MISC): A minimal set of constraints causing a given optimization solver to report infeasibility under a given set of parameters and variable settings (including initial points, tolerances, termination conditions, etc.) [138]. It is also defined as the smallest subset of constraints whose removal makes the remaining model feasible, or whose relaxation makes the original model feasible [139]-[140]. In order to make an infeasible problem feasible, all constraints in MISC should be removed or relaxed simultaneously from the problem formulation.

Irreducible Infeasible Subset (IIS): The (small) subset of constraints that is itself infeasible but becomes feasible if one or more constraints are removed from it. It is also called irreducible inconsistent subset. It is important to note that there exist more than one IIS for a given infeasible problem, and each IIS may share some similar constraints. So, several IIS's need to be calculated and post-processed to find the MISC. Currently, efficient implementations for IIS isolation are only available for linear optimization [141].

Critical Constraint Set (CCS): The minimum set of security constraints that prevents the operator from devising a feasible dispatch for a given operating priority is defined as CCS in the thesis. Remaining constraints are treated as noncritical and represented by noncritical constraint set (NCCS). While the constraints in CCS are denoted as critical constraints (CCs), constraints in NCCS are denoted as noncritical constraints (NCCs). The violations of CCs are represented by critical constraint violations (CCVs) and the violations of NCCs are represented by noncritical constraint violations (NCCVs).

From the operational viewpoint, critical constraints can help operators in two potential ways:

a) Operators can call for additional (e.g. emergency) control reserves at the locations which are more efficient for removing the critical constraints, so that SCM can be performed with reduced risk and/or cost.
b) If additional reserves are not available, the operator can relax these critical constraints by a specific amount, until the additional reserves come online, or until the original problem is resolved (e.g. faulted line back into service).

There are reliable methods to find MISC for linear optimization problems, but not for nonlinear nonconvex optimization problems, because calculation of MISC is an NP-hard problem [139]. Hence, existing methods can calculate mostly an IIS rather than MISC for nonlinear nonconvex optimization problems. Moreover, the existing methods make several assumptions on problem formulations (e.g. the problem needs to be quadratic and convex) [142].

Infeasibility diagnosis is one of the important and under-addressed issue in power system optimization models, especially nonlinear OPF formulations [2]-[5]. There are very few works on infeasibility diagnosis in nonlinear OPF formulations, focusing on constraint relaxation, soft penalization, and virtual generators (detailed literature is covered in Chapter 5) [6, 73, 81, 83-89].

Chapter 5 proposes a metaheuristic framework to analyse infeasible SCM cases. The framework does not make any assumptions on problem formulation and considers the SCM problem as a nonlinear and nonconvex optimization problem. The framework can reliably find the MISC for most of the infeasible cases, and resolve infeasibility by either relaxing or penalizing the MISC. This approach of debugging infeasible SCM and OPF models through identification of MISC, to the best of author's knowledge, is introduced for the first time in this thesis.

3.3.5 Infeasibility Measures

From an optimization perspective, the inclusion or exclusion of objective function does not modify the search space of the original infeasible problem. Hence, in the case of an infeasible optimization problem, the objective of the optimization process is to minimize the infeasibility measure. Infeasibility measures quantify the severity of infeasibility. There exist few infeasibility measures in the literature and the most popular ones are explained below.

For ease of explanation, consider only a set of inequality constraints:

$$x_i < x_{max,i} \mid \ x = 1,2,3, \dots N \tag{3.14}$$

Constraint x_i is said to be violated if $x_i > x_{max,i}$, and if a constraint is violated, infeasibility count (INFC) and infeasibility amount (INFA) can be computed as below [17, 138].

$$INFC_i = \begin{Bmatrix} 1 \mid x_i > x_{max} \\ 0 \mid x_i < x_{max} \end{Bmatrix} \tag{3.14}$$

$$INFA_i = \begin{Bmatrix} x_i - x_{max} \mid x_i > x_{max} \\ 0 \quad \mid x_i < x_{max} \end{Bmatrix} \tag{3.14}$$

a) **The number of infeasibilities (NINF):** The total number of constraints whose violation exceed the threshold limit (i.e. x_{max}).

$$NINF \ = \sum_{i=1}^{N} INFC_i \tag{3.15}$$

b) **The sum of infeasibilities (SINF):** The sum of violation of all active constraints.

$$SINF \ = \sum_{i=1}^{N} INFA_i \tag{3.16}$$

c) **The sum of squares of infeasibility (SSINF):** the sum of squares of violation of all active constraints.

$$SSINF \ = \sum_{i=1}^{N} (INFA_i)^2 \tag{3.17}$$

3.4 Solution Methods

SCM problem, (3.1)-(3.3), is a constrained optimization problem that constitutes a function to be optimized and a set of equality and inequality constraints to be satisfied. The constraints can be of a bound or functional type, and functional constraints can be linear or nonlinear. Bound constraints can be enforced on either independent variables or dependent variables. Independent variables are simply the control/search variables (e.g. generator bus voltage, generator active power, etc.) that can be directly controlled by the optimization method. Dependent variables are the variables that cannot be directly controlled by the optimization algorithm, but they are the outcomes during the optimization process (e.g. load bus voltage).

Let say the optimal value of the objective function (f) is f^* at the optimal control point (U^*) in an n-dimensional control space. Then, SCM problem can be treated as a search problem with objective to find the U^* that provides $f*$. In general, any search method starts from an arbitrary control point (U_0) in the control space and reaches U^* by incrementally moving from one location to another location in the control space. Based on the way the incremental movement is directed, search methods are divided into direct and indirect search methods.

Direct search methods, as the name says, directly regulate the incremental movement (mostly) by stochastic principles. These stochastic principles do not rely on any topological information of the problem being optimized, except the value of the objective function. In indirect search methods, as the name says, the incremental movement is guided by the gradients of the objective function and constraint functions. That is why indirect search methods are denoted as gradient-based approaches, and direct search methods are denoted as gradient-free approaches in the literature. Gradient-based approaches are also called conventional methods, while gradient-free approaches are called non-conventional or metaheuristic methods.

None of the indirect/conventional or direct/metaheuristic methods can solve a constrained problem in its original formulation, (3.1)-(3.3), as most of these algorithms are developed to solve only unconstrained optimization problems. Hence, irrespective of type of the approach to be implemented, the fundamental step in solving any constrained optimization problem is to convert the constrained optimization problem into an unconstrained optimization problem, so that the existing unconstrained optimization algorithms can be applied.

This conversion process involves addition of equality and inequality constraints to the main objective function using (interior/exterior) penalty functions. The resulting augmented function is the summation of main/original objective function and penalty for violated constraints. The augmented objective function is denoted as Lagrangian function (L, in case of gradient-based algorithms) or penalized objective function (POF, in case of metaheuristic algorithms), based on the way constraints are handled.

The objective of the modified problem is to minimize the Lagrangian or penalized objective function. Optimum of Lagrangian function (L) and original objective function (f) are identical when the penalty for violating constraints becomes zero (i.e. none of the constraints are active/unresolved in the final solution). Direct and indirect search algorithms employ different steps to minimize the Lagrangian function.

Metaheuristic methods minimize the penalized objective function directly by continuously modifying the search variables within the given bounds using stochastic principles. In other words, direct search algorithms start with an initial solution vector (guessed or random) and continuously shift the solution vector from one point to another in n-dimensional control space, as long as the objective function reduces, while penalised constraints are met. The point to note is that the trajectory of the solution vector is guided by stochastic principles, which are independent of the problem.

Conventional methods, unlike metaheuristic methods, cannot minimize the Lagrangian function (or any function, in general) directly, because there is no conventional method that can solve an inequality. Hence, conventional methods rather than directly minimizing the Lagrangian, they first derive a set of nonlinear or linear equations (so-called optimality conditions) using principles of calculus. Later, they repeatedly solve these equations using equation solvers (e.g. Newton Raphson method) as long as the objective value reduces, and constraints are met.

3.4.1. Overview of Conventional Algorithms

Conventional optimization methods are general purpose search methods, which can be applied to a wide variety of optimization problems. They use deterministic rules (e.g. line or trust region search, [143]) to explore the search space of the problem.

Their solution process involves various stages (Figure *3.1*): a) Lagrangian formulation, b) Optimality conditions derivation, and c) Solution of optimality conditions. The original problem undergoes a couple of transformations before being solved, because each stage may require usage of another method or solver. The description of the various stages is given below.

a) **Lagrangian or KKT formulation:** This phase transforms the original constrained optimization problem into an unconstrained optimization problem using various penalty functions. The resulting formulation is denoted as Lagrangian or KKT formulation of original constrained optimization problem. There are two general types of penalty functions: interior penalty functions and exterior penalty functions.

b) **Derivation of optimality conditions**: This phase derives optimality conditions for the unconstrained optimization problem in KKT formulation phase. This process requires the calculation of gradients and Hessians of the objective and constraint functions. The outcome of the process is a set of nonlinear equations, and some conditions to confirm the optimality after solving the nonlinear equations.

c) **Solution of optimality conditions:** This phase repeatedly solves the set of nonlinear equations until the optimal feasible point is found. The nonlinear equation set is generally solved by an equation solver, unless they can be solved analytically. If the equations are solved by equation solvers (e.g. Newton Raphson, Gradient method, etc.), this phase further requires the gradients of the equations and a good initial point.

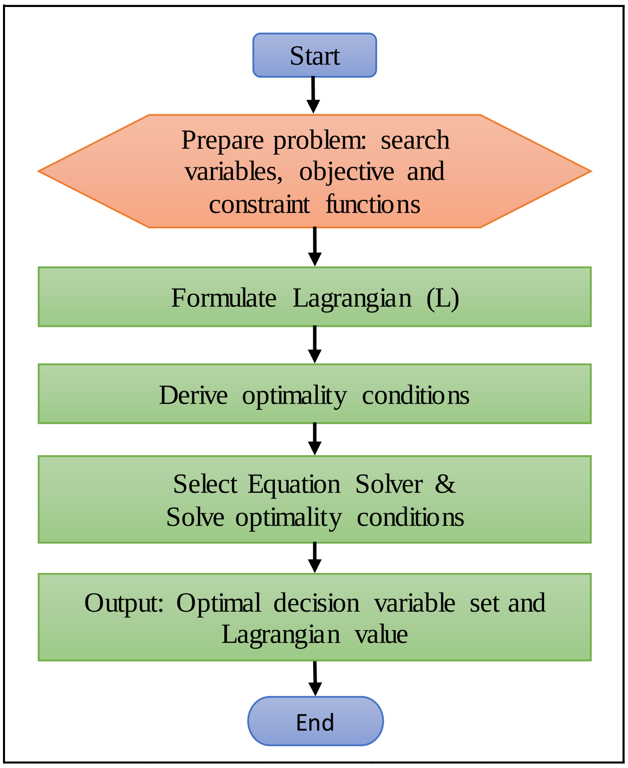


Figure 3.1 Various stages in conventional algorithms

As the conventional methods rely on gradients of the objective and constraints functions, they require the relevant functions to be continuous. Conventional methods may diverge or report infeasibility due to improper or poor initial point, especially for narrow feasible spaces (e.g. power system optimization model under peak load conditions). Moreover, conventional methods cannot diagnose and localise the infeasibility if the nonlinear optimization problem is or becomes infeasible.

3.4.2. Overview of Metaheuristic Algorithms

Metaheuristic methods are general purpose search algorithms, which can be also applied to a wide variety of optimization problems. Metaheuristic methods can be considered as “black-box”, or “problem-independent and plug-and-play type” algorithms, as they rarely rely on the nature of the considered problem.

Like conventional methods, metaheuristic algorithms also cannot solve the constrained optimization problems directly. The original formulation must be transformed into an unconstrained optimization problem using penalty functions (Figure *3.2*). This step is essentially the same as the Lagrangian formulation in conventional methods, but the resulting objective function is called Penalized Objective Function (POF). While conventional algorithms employ deterministic rules to explore the problem space, metaheuristic algorithms employ guided stochastic search.

Metaheuristic algorithms initially generate a random feasible set of decision vectors, which are called “population”, “swarm”, etc. Afterwards, they apply various stochastic manipulations or operations (depending on the formulated algorithm) to find the next solution point(s) in the search space. This process is repeated until the predefined termination criterion is met.

In general, metaheuristic algorithms can be classified into three groups: evolutionary computation, swarm intelligence, and physics inspired algorithms. This thesis implements three algorithms: genetic algorithm from evolutionary computation, simulated annealing from physics inspired algorithms, and particle swarm optimization from swarm intelligence algorithms to analyze SCM problem.

Unlike conventional methods, metaheuristic algorithms are insensitive to the selection of initial values, but like conventional algorithms, they can also find (near) optimal solutions. Despite their advantages, however, none of the metaheuristic algorithms has seen a practical implementation in the power industry, even for off-line analysis of electrical networks. The two most likely reasons for this are: a) from algorithm implementation perspective, metaheuristic algorithms are computationally more intensive and generally lack a clear analytical understanding and ensuring of convergence criteria, and b) from practical implementation perspective, there is still no clear set of instructions that could inform network planners and operators for exactly what system studies and under what system operating conditions metaheuristic algorithms could provide real benefits over conventional methods. Conversely, this thesis shows some of the realistic benefits of metaheuristic algorithms.

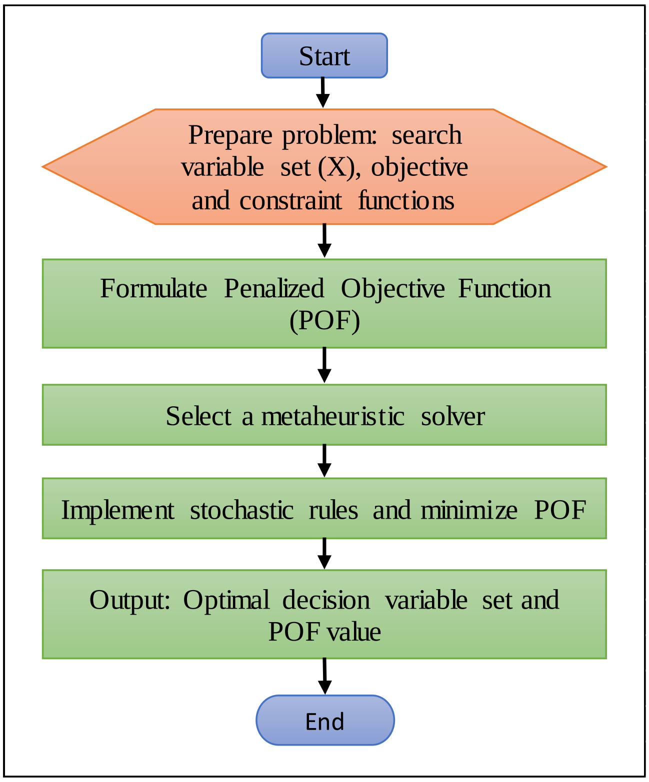


Figure 3.2 Various stages in metaheuristic algorithms

a) Evolutionary Computation

The family of algorithms that is designed based on the simplified simulation of biological evolution are denoted as evolutionary computation, or simply evolutionary algorithms [36]. The evolution of population over the generations is simulated using the evolutionary principles: natural selection, recombination, and mutation. In biological evolution, population undergoes natural selection, recombination and mutation, and then next generation population is created. As in the nature, the evolution process repeats until only the best performing individuals survive in the last considered generation.

The simulation of evolutionary process can be used to find high quality solutions to an optimization, or search problem [144]. The candidates in the population set represent a set of solutions to the given problem. Evolutionary algorithms are considered population-based metaheuristic algorithms, because a set of population is used to perform parallel search to find the optimal solution.

In evolutionary algorithms, a set of solution candidates (i.e. initial population) is generated randomly and then the initial population undergoes through natural selection, recombination, and mutation to produce the next generation of population. A fitness function is used to evaluate the "quality" of solutions, which helps during the selection process. The overall evolution process will be carried out repeatedly until some stopping criteria are met. The stopping criteria can be: maximum number generation, (pre)specified solution accuracy, computational time, etc.

The idea of using evolutionary principles to solve a problem date back to 1950s [145]. While there are numerous evolutionary algorithms and researchers are continuously trying to develop novel evolutionary algorithms (Table 3.1), few of these algorithms (e.g. evolutionary programming, genetic programming, genetic algorithm, and evolutionary strategy) are popular and have been applied to several problems. A more detailed information on evolutionary computation algorithms can be found in [144].

Table 3.1 A List of Evolutionary Algorithms

Genetic Algorithms (GA)
Genetic Programming (GP)
Evolutionary Programming (EP)
Evolutionary strategies (ES)
Differential Evolution (DE)
Natural evolution strategies (NES)
Memetic Algorithms (MA)
Cultural Algorithms (CA)
Covariance matrix adaptation evolution strategy (CMA-ES)

b) Physics Inspired Algorithms

Physics-inspired metaheuristics algorithms are designed based on the simplified simulation of a physical process or phenomenon. These algorithms employ basic principles of physics (e.g. Newton's gravitation law, motion law, etc.) to simulate a phenomenon [146]. For example, simulated annealing algorithm employs thermodynamic principle to simulate the annealing process in material science field. The list of popular physics inspired algorithms is given in Table 3.2. A more detailed information on physics inspired algorithms can be found e.g. in [146]-[147].

Table 3.2 List of Physics Inspired Algorithms

Name of Algorithm	Field of inspiration
Simulated Annealing	Thermodynamics
Colliding Bodies Optimization (CBO)	Newton's laws of motion
Gravitational Search Algorithm (GSA)	Newton's gravitational force
Central Force Optimization (CFO)	Newton's gravitational force
Space Gravitation Optimization (SGO)	Newton's gravitational force
Gravitational Interaction Optimization (GIO)	Newton's gravitational force
Big Bang–Big Crunch search (BB–BC)	Celestial mechanics and astronomy
Black Hole Search (BHS)	Celestial mechanics and astronomy
Galaxy-based Search Algorithm (GbSA)	Celestial mechanics and astronomy
Artificial Physics-based Optimization (APO)	Celestial mechanics and astronomy
Integrated Radiation Search (IRS)	Celestial mechanics and astronomy
Electromagnetism-like Optimization (EMO)	Electromagnetism
Charged System Search (CSS)	Electromagnetism
Hysteretic Optimization (HO)	Electromagnetism
Ray Optimization (RO)	Optics
Harmony Search Algorithm (HSA)	Acoustics
Water Drop Algorithm (WDA)	Hydrology and hydrodynamics
River Formation Dynamics Algorithm (RFDA)	Hydrology and hydrodynamics
Water Cycle Algorithm (WCA)	Hydrology and hydrodynamics

c) Swarm Intelligence Algorithms

The family of algorithms based on the simulation of collective, or social behaviour of the individuals (i.e. particles, or agents) with the environment, or with each other within a given social system, are denoted as swarm-intelligence based optimization algorithms. The agents are typically distributed over the environment and hence their cooperation leads to collective intelligence [148]. The list of popular swarm intelligence algorithms is mentioned in Table 3.3, while more information on swarm intelligence algorithms can be found in [149]-[150].

Table 3.3 List of Swarm Intelligence Algorithms

Particle Swarm Optimization (PSO)
Ant Colony System (ACS)
Stochastic Diffusion Search (SDS)
Bacteria Foraging (BF)
Artificial Bee Colony (ABC)
Glow-worm Swarm Optimization (GSO)
Cuckoo Search Algorithm (CSA)

3.5 Penalty Functions

Constraint handling is crucial for the performance of an optimization algorithm. A poor constraint handling may drive the search into the suboptimal or infeasible region, which is more likely when the search space is limited (e.g. contingency analysis). As most of the optimization algorithms in original form can only be applied to unconstrained problems, constrained problems must be transformed into an unconstrained problem. While the equality constraints are always modelled with Lagrangian multipliers, inequality constraints are modelled mostly with penalty functions.

Penalty functions transform the original constrained problem into a sequence of unconstrained problems by adding/subtracting a certain value (i.e. penalty) to/from the objective function based on the amount of constraint violation. When all the solution candidates are feasible, the optimum unconstrained optimization problem will also be a local optimum for the original constrained optimization problem.

In general, irrespective of conventional and non-conventional methods, there exist two types of penalty functions: exterior and interior penalty functions [151]. Interior penalty functions initially guide the unconstrained search (mostly) from a feasible region and then force the search to stay away from the constraint boundary by applying a penalty. The more the distance from the interior of the boundary the less penalty will be applied. The penalty will be extremely high when the search is on the boundary or exterior of the boundary. Thus, if a solution starts within a feasible region subsequent points are forced to be within the feasible region since the constraint boundaries act as barriers during the optimization process. That is why interior penalty functions are also called as barrier and hard penalty functions.

Exterior penalty functions initially guide the unconstrained search (mostly) from an infeasible region and then force the search to move towards feasible region by applying heavy penalties. As the exterior penalty functions accept the infeasible points more than the interior penalty functions, these are also called soft penalty functions. The main difference between exterior and interior penalty functions is that exterior penalty functions penalize only infeasible solutions, but the interior penalty functions penalize both feasible and infeasible solutions. Although interior penalty functions work very well over soft and hard constraints, they may fail to find a solution when the problem is over-constrained with many hard constraints. As the exterior penalty functions are, in principle, insensitive to soft and hard constraints, metaheuristic algorithms use these functions to model both equality and inequality constraints.

This thesis employs three types of exterior penalty functions (step, linear and quadratic) and one interior penalty function (log barrier) to model inequality constraints. But the equality constraints are modelled using Lagrangian multipliers. The mathematical formulation of considered penalty functions is explained below [151]-[154].

Log Barrier Penalty Functions (BPF)

$$\phi_{BPF} = \begin{pmatrix} -\log(x - x_{min}) \ or \ -\log(x - x_{max}) & \left| x > x_{min} \ or \ x < x_{max} \right. \\ 10^{20} & \left| x < x_{min} \ or \ x > x_{max} \right. \end{pmatrix} \quad (3.18)$$

$$x \in [P_g \ Q_g \ V \ S_{ij}] \quad (3.19)$$

$$x_{min} \in [P_{gmin} \ Q_{gmin} \ V_{min} \ S_{ij,min}] \quad (3.20)$$

$$x_{max} \in [P_{gmax} \ Q_{gmax} \ V_{max} \ S_{ij,max}] \quad (3.21)$$

Step Penalty Functions (SPF)

$$\phi_{SPF} = \left\{ \begin{matrix} K_{Pg}^{Itr} \\ K_{Qg}^{Itr} \\ K_{V}^{Itr} \\ K_{S}^{Itr} \end{matrix} \left| \begin{matrix} P_g < P_{gmin} \ or \ P_g > P_{gmax} \\ Q_g < Q_{gmin} \ or \ Q_g > Q_{gmax} \\ V < V_{min} \ or \ V > V_{max} \\ S_{ij} > S_{ij,max} \end{matrix} \right. \right\} \quad (3.22)$$

Linear Penalty Functions

$$\phi_{LPF} = \left\{ \begin{array}{c|c} K_{Pg}^{Itr}(P_{gmin} - P_g) or\ K_{Pg}^{Itr}(P_g - P_{gmax}) & P_g < P_{gmin}\ or\ P_g > P_{gmax} \\ K_{Qg}^{Itr}(Q_{gmin} - Q_g) or\ K_{Pg}^{Itr}(Q_g - Q_{gmax}) & Q_g < Q_{gmin}\ or\ Q_g > Q_{gmax} \\ K_V^{Itr}(V_{min} - V) or\ K_{Pg}^{Itr}(V - V_{max}) & V < V_{min}\ or\ V > V_{max} \\ K_S^{Itr}(S_{ij} - S_{ij,max}) & S_{ij} > S_{ij,max} \end{array} \right\}$$

(3.23)

Quadratic Penalty Functions (QPF)

$$\phi_{QPF} = \left\{ \begin{array}{c|c} K_{Pg}^{Itr}(P_{gmin} - P_g)^2 or\ K_{Pg}^{Itr}(P_g - P_{gmax})^2 & P_g < P_{gmin}\ or\ P_g > P_{gmax} \\ K_{Qg}^{Itr}(Q_{gmin} - Q_g)^2 or\ K_{Pg}^{Itr}(Q_g - Q_{gmax})^2 & Q_g < Q_{gmin}\ or\ Q_g > Q_{gmax} \\ K_V^{Itr}(V_{min} - V)^2 or\ K_{Pg}^{Itr}(V - V_{max})^2 & V < V_{min}\ or\ V > V_{max} \\ K_S^{Itr}(S_{ij} - S_{ij,max})^2 & S_{ij} > S_{ij,max} \end{array} \right\}$$

(3.24)

Where:

P_g, Q_g, V, S_{ij} – active and reactive generation, bus voltage, MVA flow in a line between bus *i* and bus *j*

$P_{gmin}, Q_{gmin}, V_{min}, S_{ij,min}$ – minimum limit on P_g, Q_g, V, S_{ij}

$P_{gmax}\ Q_{gmax}\ V_{max}\ S_{ij,max}$– maximum limit on P_g, Q_g, V, S_{ij}

K_{Pg}^{Itr} – Penalty factor for to active power generation violation at iteration Itr

K_{Qg}^{Itr}– Penalty factor for reactive power generation violation at iteration Itr

K_V^{Itr}– Penalty factor for voltage constraint violation at iteration Itr

K_S^{Itr} – Penalty factor for line MVA flow violation at iteration Itr

3.6 Implemented Algorithms

3.6.1 Newton Raphson Method with Interior and Exterior Penalty Functions

This thesis implements or utilizes a couple of conventional approaches or solvers (Table 3.4) to analyse SCM problems. All the utilized approaches, by default, employs Newton-Raphson method to solve KKT conditions. The general Lagrangian formulation and KKT (or optimality) conditions that are applicable to all types of implemented approaches are presented in this section. PSS/E OPF solver, unless otherwise specified, is used as the default conventional solver to evaluate the performance of proposed approaches in this thesis.

Table 3.4 List of Employed Conventional Solvers

Solver Name	Employed Approach	Comments
PSSE	Exterior and interior point method	Siemens [155]
IPAM	Interior point algorithm	MathWorks [156]
MIPS	Primal-dual Interior point solver	Matpower [157]
FMINCON	Interior point method	MathWorks [156]
PDIPM	Primal-dual interior point method	Matpower [158]
SCPDIPM	Step-controlled primal-dual interior point method	Matpower [158]
TRALM	Trust region based augmented Lagrangian method	Matpower [158]

3.6.1.1 Lagrangian Formulation

There exist several ways to formulate the Lagrangian function and hence optimality conditions, based on the way the constraints are handled. It is often very difficult for power system engineers (especially early state researchers) to make a constructive relationship between these formulations as well as to get an intuitive understanding of these formulations. With an aim to provide an intuitive understanding, this thesis classifies the Lagrangian formulations into three types which are explained below.

Let's consider a general nonlinear optimization problem, (3.25)-(3.27).

$$min\ f(x) \tag{3.25}$$

$$\text{s.to.} \quad g(x) = 0 \tag{3.26}$$

$$h(x) < 0 \tag{3.27}$$

Where: decision variable $X = [x]$

A. Traditional Formulation using Lagrangian and KKT multipliers

This approach does not employ any of the penalty functions to model either equality or inequality constraints. But this approach requires both g and h to be continuous functions (at least the order of two) which may not be possible always (e.g. h may be a bound inequality constraint). Moreover, the optimization process, in this case, is quite complicated and slow because it requires checking of μ and h regularly.

$$L(x,.) = f + \Phi_{eq}(g,\lambda) + \Phi_{ineq}(h,\mu)$$

$$\Longrightarrow L(x,\lambda,\mu) = f + \lambda g + \mu h \tag{3.28}$$

Where: $\Phi_{eq}(g,\lambda) = \lambda g$

$$\Phi_{ineq}(h, \mu) = \mu h$$

$$X = [x, \lambda, \mu]$$

B. Interior Penalty Functions based Formulation

i) Primal Interior Penalty Methods

This approach employs Lagrangian multipliers (λ) to model equality constraints and interior penalty functions to model inequality constraints. This approach does not require h be to continuous, but it requires g to be continuous. The dimensionality of the Lagrangian in this case (3.29) is lower than (3.28) because the number of decision variables is less. One should note that μ is a barrier parameter but not the decision variable, hence its value is not calculated by the optimization process. The μ starts with a very high value and reduced gradually over the iterations by the predefined logic (i.e. by the programmer). If h is a functional constraint, in some cases, it might be difficult or computational inefficient to calculate its gradient and hessian with logarithmic function included. This problem can be avoided by converting functional inequality constraint into an equality constraint through slack (or dual) variables, which is discussed in the next approach.

$$L(x, .) = f + \Phi_{eq}(g, \lambda) + \Phi_{ineq}(h, \mu)$$

$$\Longrightarrow L^{\mu}(x, \lambda) = f + \lambda g + \mu \log(-h) \tag{3.29}$$

Where:

$$\Phi_{eq}(g, \lambda) = \lambda g$$

$$\Phi_{ineq}(h, \mu) = \mu \log(-h)$$

$$X = [x, \lambda]$$

ii) Primal-Dual Interior Penalty Methods

This method reformulates the original optimization problem by converting functional inequality constraints into equality constraints through slack variables (shown below). Later on, this method employs Lagrangian multipliers to model (modified) equality constraints and Log barrier penalty functions to model inequality bound constraints. Same as before, μ is a barrier parameter but not a decision variable.

$$h < 0 \Longrightarrow h + s = 0;\ s > 0 \qquad\qquad min\, f(x)$$

$$G(x,s)=\begin{Bmatrix} g \\ h+s \end{Bmatrix}=0 \qquad \Longrightarrow \qquad G(x,s)=0$$

$$H(s)=\{-s\}<0 \qquad\qquad H(s)<0$$

$$L(x,.)=f+\Phi_{eq}(G,\lambda)+\Phi_{ineq}(H,\mu)$$

$$\Rightarrow L^{\mu}(x,\lambda,s)=f+\lambda G+\mu\log(-H)$$

$$\Rightarrow L^{\mu}(x,\lambda,s)=f+\lambda G+\mu\log(s) \tag{3.30}$$

Where:
$$\Phi_{eq}(G,\lambda)=\lambda G$$

$$\Phi_{ineq}(H,\mu)=\mu\log(s)$$

$$X=[x,\lambda,s]$$

C. Exterior Penalty Functions based Formulation

i) Primal Exterior Penalty Methods

This approach uses Lagrangian multipliers (λ) to model equality constraints and exterior penalty functions to model inequality constraints. Anyone of the three exterior penalty functions: step (SPF), linear (LPF), and quadratic penalty functions (QPF) can be employed in this case. It should be noted that μ is neither a decision variable nor a barrier parameter. It represents the penalty coefficient for violating a specific inequality constraint. It could be fixed or dynamic (e.g. gradually increases), nevertheless its value is decided by a predefined logic rather than the optimization process.

$$L(x,.)=f+\Phi_{eq}(g,\lambda)+\Phi_{ineq}(h,\mu)$$

$$\Rightarrow L^{\mu}(x,\lambda)=f+\lambda g+\Phi_{ineq}(h,\mu) \tag{3.31}$$

Where:
$$\Phi_{eq}(g,\lambda)=\lambda g$$

$$\Phi_{ineq}^{SPF}(h,\mu)=\begin{Bmatrix} 0 & \Big| & h<0 \\ \mu & & h>0 \end{Bmatrix}$$

$$\Phi_{ineq}^{LPF}(h,\mu)=\begin{Bmatrix} 0 & \Big| & h<0 \\ \mu h & & h>0 \end{Bmatrix}$$

$$\Phi_{ineq}^{QPF}(h, \mu) = \left\{ \begin{array}{c|c} 0 & h < 0 \\ \mu h^2 & h > 0 \end{array} \right\}$$

$$X = [x, \lambda]$$

ii) Primal-Dual Exterior Penalty Functions

This method, same as primal-dual interior penalty methods, reformulates the original optimization problem by converting functional inequality constraints into equality constraints through slack variables (shown below). Later on, this method employs Lagrangian multipliers to model (modified) equality constraints and one of the three exterior penalty functions to model inequality bound constraints. Again, μ is neither a decision variable nor a barrier parameter. While the barrier parameter basically starts with a high value and gradually decreases (ideally becomes zero at a feasible optimal solution), penalty coefficient can be either fixed or gradually increases until the constraints are satisfied. But once a constraint is satisfied, penalty coefficient for that constraint becomes zero.

$$\begin{array}{ccc} h < 0 \Rightarrow h + s = 0;\ s > 0 & & \min f(x) \\ G(x,s) = \left\{ \begin{matrix} g \\ h + s \end{matrix} \right\} = 0 & \Longrightarrow & G(x,s) = 0 \\ H(s) = \{-s\} < 0 & & H(s) < 0 \end{array}$$

$$L(x, .) = f + \Phi_{eq}(G, \lambda) + \Phi_{ineq}(H, \mu)$$

$$\Rightarrow L^{\mu}(x, \lambda, s) = f + \Phi_{eq}(G, \lambda) + \Phi_{ineq}(H, \mu)$$

$$\Rightarrow L^{\mu}(x, \lambda, s) = f + \lambda G + \Phi_{ineq}(H, \mu) \tag{3.32}$$

Where: $$\Phi_{eq}(G, \lambda) = \lambda G$$

$$\Phi_{ineq}^{SPF}(H, \mu) = \left\{ \begin{array}{c|c} 0 & H < 0 \\ \mu & H > 0 \end{array} \right\}$$

$$\Phi_{ineq}^{LPF}(H, \mu) = \left\{ \begin{array}{c|c} 0 & H < 0 \\ \mu h & H > 0 \end{array} \right\}$$

$$\Phi_{ineq}^{QPF}(H, \mu) = \left\{ \begin{array}{c|c} 0 & H < 0 \\ \mu h^2 & H > 0 \end{array} \right\}$$

$$X = [x, \lambda, s]$$

3.6.1.2 Optimality Conditions and Newton Step

This section derives the optimality conditions for one type of Lagrangian function and similar conditions can be easily derived for other Lagrangian functions.

Consider a Lagrangian function as below

$$L(x, \lambda, \mu) = f + \lambda g + \mu h \tag{3.33}$$

Taking the partial derivatives of (3.33) with respect to each of the variables yields the first-order optimality conditions:

$$L_x = f_x + \lambda g_x + \mu h_x = 0 \tag{3.34}$$

$$L_\lambda = g = 0 \tag{3.35}$$

$$L_\mu = h = 0 \tag{3.36}$$

The above equations represent a family of nonlinear equations which must be solved to find a stationary point (this may or may not be the optimal). In general, Newton Raphson (NR) or similar equation solvers are used to solve these equations. In order to apply the NR, (3.33) -(3.35) must be linearized with respect to each variable. This is also equivalent to Taylor series expansion of (3.34)-(3.36), but only first two terms are considered.

$$\Rightarrow L_x + L_{xx}\,\Delta x + L_{x\lambda}\Delta\lambda + L_{x\mu}\,\Delta\mu + \cdots = 0$$
$$\Rightarrow L_\lambda + L_{\lambda x}\,\Delta x + L_{\lambda\lambda}\Delta\lambda + L_{\lambda\mu}\,\Delta\mu + \cdots = 0$$
$$\Rightarrow L_\mu + L_{\mu x}\,\Delta x + L_{\mu\lambda}\Delta\lambda + L_{\mu\mu}\,\Delta\mu + \cdots = 0$$
$$\Rightarrow \begin{bmatrix} L_{xx} & L_{x\lambda} & L_{x\mu} \\ L_{\lambda x} & L_{\lambda\lambda} & L_{\lambda\mu} \\ L_{\mu x} & L_{\mu\lambda} & L_{\mu\mu} \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta\lambda \\ \Delta\mu \end{bmatrix} = -\begin{bmatrix} L_x \\ L_\lambda \\ L_\mu \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} f_{xx} + \lambda g_{xx} + \mu h_{xx} & g_X & h_x \\ g_x & 0 & 0 \\ h_x & 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta\lambda \\ \Delta\mu \end{bmatrix} = -\begin{bmatrix} f_x + \lambda g_x + \mu h_x \\ g \\ h \end{bmatrix} \tag{3.37}$$

$$J\Delta X = B \tag{3.38}$$

Where: J – Newton Jacobian, B – correction matrix, ΔX – correction for X.

For any initial solution X, the next point (X') can be calculated as follows

$$X' = X + \Delta X \tag{3.39}$$

Equation (3.38) and (3.39) represents the Newton steps. If $X^* = [x^*, \lambda^*, \mu^*]$ is a local optimum for the problem, it must satisfy the following optimality conditions [157]-[159].

Stationarity conditions:

$$L_x(X^*) = 0 \tag{3.40}$$

Primal feasibility conditions:

$$g(X^*) = 0 \tag{3.41}$$

$$h(X^*) < 0 \tag{3.42}$$

Dual feasibility conditions:

$$\mu > 0 \tag{3.43}$$

Complementary slackness condition:

$$\mu h(X^*) = 0 \tag{3.44}$$

3.6.2 Genetic Algorithm

Genetic algorithm is an evolutionary algorithm inspired by the Darwinian principle of natural evolution of species through (genetic) selection [160]-[161]. The initial principle of the genetic algorithms is proposed in 1975 [162]. Since then, researchers proposed numerous variations of the genetic algorithms, making genetic algorithms as the most widely known and applicable type of metaheuristic algorithms [163]. Over the last couple of decades, genetic algorithm has been applied to solve numerous optimization problems in power systems engineering: unit commitment [164], economic dispatch [165], optimal power flow [166], volt/var control [167], transmission expansion planning [168], capacitor placement [169], etc.

Genetic algorithm (GA) begins with an initial population of individuals, often created randomly. The set of solution candidates are denoted as chromosomes or phenotypes and each chromosome could be a potential solution to a given problem. The elements of chromosome are denoted as genes and the number of genes is equal to the number of decisions, or search variable. In canonical GA, each gene is represented by a string of binary bits. The initial population undergoes through genetic operations (selection, crossover, and mutation) to produce the next generation of the population. New population again undergoes through genetic operations to produce further generation and the process is repeated until some predefined stopping criteria are met (Algorithm 3.1).

In each generation, fitness of every individual is evaluated, typically regarding the value of the objective function to be optimized. During the selection process, a proportion of individuals, denoted as intermediate population, are stochastically selected from the current population. The chromosomes or individuals with a higher fitness have more chance to be selected for reproduction than with lower fitness. Pair of randomly chosen parents from the intermediate population are combined through crossover operation to reproduce the offspring. In other words, crossover operation modifies the chromosomes between the parents to create offspring. Crossover operation is repeated until the size of the offspring becomes equal to the size of the population. Mutation operation involves alteration of one or more genes of probabilistically chosen chromosome from the offspring. The modified offspring after the mutation operation is considered as new generation of population. There are numerous types of selection, crossover, and mutation operators in existing literature, with the notable ones mentioned in Table 3.5. This thesis implements a real-coded genetic algorithm and the main steps involved in implementing GA to SCM problems are explained as Algorithm 3.1.

Table 3.5 Types of selection, crossover, and mutation operators

Selection Types [170]	Crossover Types [171]	Mutation Types [172]
Roulette-wheel selection Rank selection Tournament selection Truncation selection Reward-based selection Stochastic universal sampling	1. Single-point 2. Two-point 3. Three-parent 4. Linear	1. Bit spring 2. Flip bit 3. Boundary 4. Nonuniform 5. Uniform 6. Gaussian 7. Shrink

Algorithm 3.1: Genetic Algorithm Implementation to SCM Problem

1: Define problem settings: list of control variables, objective function, type of penalization

2: Formulate original (unpenalized) and penalized (Lagrangian) objective functions

3: Set GA parameters: population size, and types of selection, crossover, and mutation

4: Generate initial population (i.e. initial solution set)

5: Execute power flow and compute original objective value

6: Evaluate constraints: record violated constraints and violation amount

7: Compute penalized objective value

8: ***While*** none of the termination criteria is met ***do***

9: Perform ***selection*** operation

10: Perform ***crossover*** operation

11: Perform ***mutation*** operation

12: Update population

13: Execute power flow and compute original objective at updated population

14: Evaluate constraints: record violated constraints and violation amount

15: Compute penalized objective value

16: ***end while***

17: Output: control variable setpoints, objective value, and active constraints with violation amount

3.6.3 Simulated Annealing

Simulated annealing (SA) is a physics-inspired metaheuristic algorithm, which mimics the annealing process in metallurgy. Annealing involves heating up a material until it melts and cooling it down slowly [173]. The heating and controlled cooling of a material is aimed to increase the size of its crystals and reduce imperfections. The energy gained by heating enables atoms to change their configurations freely, while the controlled slow cooling-schedule guide the atoms to ultimately form the lowest energy configuration. While the controlled slow cooling brings the material to a highly ordered crystalline state of lowest energy, rapid cooling yields imperfections and glass-like intrusions inside the material [174].

In [175], simulated annealing process is initially proposed to find the minimum of a function as an equivalent to finding the lowest energy configuration. From the optimization viewpoint, the configuration indicates a solution in the search space, with the lowest energy configuration indicating the corresponding value of the fitness, or objective function. The algorithm starts with a random solution with a high temperature and then decreases the temperature gradually in steps. This temperature loop is like the iteration count in normal optimization algorithms. Initially, the random solution ($X0$) is considered as the best solution and the related fitness value is considered as the best objective value. At each temperature, metropolis algorithm is simulated some number of times to find the thermal equilibrium corresponding to that temperature.

Metropolis algorithm generates random solutions (i.e. trail solution $Xtrial$) in the neighbourhood of current solution ($Xcurrent$) and evaluates the fitness values of these solutions. The movement of atoms from the current configuration (or state/solution) to trail configuration is decided by Boltzmann distribution. In other words, the acceptability of the trial solution as a next solution is decided by Boltzmann distribution.

According to Boltzmann (3.18), the transition or acceptance probability (P_a) is equal to one, if the trail solution has lower fitness value (i.e. objective function value) than the current solution; and is equal to a value between zero and one, if the trial solution has higher fitness value than the current solution. A trial solution is accepted only when the transition probability is equal to or greater than a random value (generated between zero and one). This implies that some trial solutions are still accepted, even though they do not provide a better fitness value. Where k in (3.18) represents Boltzmann constraints and is set to one.

$$P_a = \left(\begin{matrix} 1 \\ \exp\left(\frac{f_{current} - f_{trial}}{kT}\right) \end{matrix} \middle| \begin{matrix} f_{trial} < f_{current} \\ f_{trial} > f_{current} \end{matrix} \right) \tag{3.18}$$

The ability to accept worse solutions is an inherent feature of simulated annealing, which enables it to escape from local optima. The acceptability of worse solutions depends on the cooling schedule: acceptance ratio is big at a high temperature (ideally one, at infinite temperature) and small at low temperature (ideally zero, at zero temperature). Theoretically, an optimal solution is guaranteed if the cooling schedule consists of infinite number of steps [173]. The maximum number of temperature steps is a trade-off between the solution accuracy and computational time. The overall search process will stop/terminate according to a pre-defined criterion (e.g. fitness value lower than a threshold value, computational time limit, etc.). The mathematical process of SA is explained in Algorithm 3.2.

Over the last few decades, simulated annealing algorithm has been applied to solve numerous optimization problems in power systems engineering: unit commitment [176], economic dispatch [177], optimal power flow [178], reactive power planning [179], etc. A more detailed survey of SA applications in power systems engineering is available in [180]-[181].

Algorithm 3.2: SA Algorithm Implementation to SCM Problem

Define problem settings: list of control variables, objective function, type of penalization

Formulate original (unpenalized) and penalized (Lagrangian) objective functions

Set SA parameters: Initial temperature (T_0), Boltzmann's constant (k), temperature reduction factor (t_r)

Execute power flow at the solution and compute original objective value (f_0)

Evaluate constraints: record violated constraints and violation amount

Compute penalized objective value (F_o) at (X_o)

$\boldsymbol{While}$ none of the termination criteria met $\boldsymbol{do}$

    $\boldsymbol{for}\ i = 1{:}\ number\ of\ new\ solutions$

        Generate new (random) solution (X_i)

        Evaluate X_i: execute power flow and compute objective value (f_i)

        Evaluate constraints: record violated constraints and violation amount

        Compute penalized objective value at X_i: F_i

        $\boldsymbol{if}\ F_i < F_o\ then\ X_{new} = X_i\ \ and\ F_{new} = F_i\ \ f_{new} = f_i\ \boldsymbol{else}$

            Generate a random number $R(0,1)$

            Inferior solution acceptance probability: $P_a = exp((\ F_i - \ F_0)/kT)$

            $\boldsymbol{if}\ P_a > R{:}\ X_{new} = X_i\ ;\ \ F_{new} = F_i\ ;\ \ f_{new} = f_i\ \ \boldsymbol{else}$

                $X_{new} = X_o;\ F_{new} = F_0\ ;\ f_{new} = f_o$

            $\boldsymbol{end\ if}$

        $\boldsymbol{end\ if}$

    $\boldsymbol{end\ for}$

    Reduce the temperature: $T = t_r T$

$\boldsymbol{end\ while}$

Output: control variable setpoints, objective value, and active constraints with violation amount

3.6.4 Particle Swarm Optimization

Particle Swarm Optimization is a swarm-intelligence based metaheuristic algorithm inspired by the social or collective behaviour of birds-flocking or fish-schooling. PSO algorithm is proposed in [182] and since then numerous variations are proposed by researchers. Over the last couple of decades, PSO has been applied to solve numerous optimization problems in power systems engineering: unit commitment [183]-[184], economic dispatch [185], optimal power flow [186], volt/var control [187], etc. A survey of PSO applications in power systems engineering is available in [188]-[189].

From biological system viewpoint, PSO can be explained as a search strategy followed by flock of birds searching for food in an area. While the birds do not know the location of the food, they know how far the food is in each iteration. Initially, each bird starts the journey from a random location in the given area. The birds who are closer to the food send sound signals to all other birds. The bird who sends the loudest signal is considered closest to the food and may be considered as *lead bird*. Hence, the other birds modify search direction and try to follow or circle over the *lead bird*. After topologically readjusting their position, they re-start the search. While the searching goes, the *lead role* can be maintained by the previous *lead bird* or taken by the new one, depending on who is closest to the food. This process continues until one of the birds finds the food and other birds reach that location.

From the mathematical implementation viewpoint, in PSO, a set of randomly placed particles (X) continuously explore the D-dimensional problem space by changing their velocity (V) until meeting a predefined criterion. During the search, each particle evaluates objective function at its current location (which could be a solution) and determines its further movement by combining its best-fitness location (p_{best}, *particle-best-solution*) with group best-fitness location (g_{best}, *swarm-best-solution*). The particle-best-solution is the best solution (fitness) achieved by an individual particle and each particle will have its own particle-best-solution at any time. The swarm-best-solution is best solution achieved by the total swarm. At any time, there exist only one swarm-best-solution, which is one of the particle-best-solutions at that that time.

The next iteration, $k+1$, takes place after all particles have moved in the current, k^{th}, iteration. As iterations progress, the whole swarm move closer to an optimum of the fitness function [190]. The particles' velocities and positions are updated using (3.19) and (3.20). Inertia (w) is used to control the trade-off between swarm exploration and exploitation, or global and local search capabilities. The acceleration coefficients C_1 and C_2 in (4) control the cognitive and social influence on the particle velocity. Two uniformly distributed pseudorandom numbers, r_1 and r_2, introduce randomness in particle movement. Main steps involved in implementing PSO to SCM problems are explained as Algorithm 3.3.

$$V^{k+1} = w^k . V^k + C_1 r_1 (X^k - p_{best}) + C_2 r_2 (X^k - g_{best}) \tag{3.19}$$

$$X^{k+1} = X^k + V^{k+1} \tag{3.20}$$

Algorithm 3.3: PSO Algorithm Implementation to SCM Problem

```
Define problem settings: list of control variables, objective function, type of penalization
Formulate original (unpenalized) and penalized (Lagrangian) objective functions
Set PSO parameters: swarm size, inertia weight, cognitive and social coefficients, etc.
Initialize swarm particles' positions (i.e. initial solution set)
Execute power flow and compute original objective value
Evaluate constraints: record violated constraints and violation amount
Compute penalized objective value
While none of the termination criteria is met do
    Compute particle (individual) best and swarm best position
    Update swarm velocity
    Update swarm position (i.e. updated solution set)
    Execute power flow and compute original objective at new swarm positions
    Evaluate constraints: record violated constraints and violation amount
    Compute penalized objective value
end while
Output: control variable setpoints, objective value, and active constraints with violation amount
```

3.7 Conclusions

Optimization models, especially SCM models, which are used to make planning and operation decisions in modern electricity networks, are becoming progressively larger and more complex due to increased interconnections, renewable energy penetration, complex controls, and frequent operation under stressed and even overstressed conditions. As models continue to grow larger, they can become infeasible and identifying and resolving the infeasibility becomes increasingly difficult.

It is extremely important to diagnose and localize the infeasibility not only to resolve it from optimization viewpoint, but also to identify the bottlenecks in electricity transmission and distribution networks, so that appropriate preventive and corrective actions can be devised to deal with the constraint violations. The infeasibility report generated by the commercial power system solvers (e.g. OPF solvers to solve SCM problems) are barely useful to network planners and operators and they should be equipped with improved infeasibility diagnosis tools.

In this context, this chapter presented a detailed discussion of such infeasible SCM problem formulations with underlined concepts from the optimization theory. The concept of MISC from optimization theory is introduced to help diagnose and localize infeasibility in infeasible SCM formulation. A general discussion of both conventional and metaheuristic approaches, and a detailed discussion of implemented solution algorithms are also presented in this chapter. Next chapter develops a set of feasible and infeasible SCM models that are used to validate the MISC identification framework proposed in Chapter 5.

As mentioned earlier, modern electricity networks are increasingly interfaced with inverter-interfaced renewable generation and are becoming sensitive to even small disturbances. The transitions between different steady-state equilibriums will possess completely different dynamics under the reduced inertia and damping environment, which may adversely affect the nature of dynamic security constraints that must be fulfilled during the transition. Hence, the management of security constraints is going to play a key role than ever before in the secure operation of modern electricity networks.

The important point worth mentioning is that the mathematical models representing the operation of modern electricity networks are becoming the function of non-smooth functions (e.g. mathematical models of inverter-interfaced generation, battery storage, etc). This limits the application of conventional gradient approaches to performing security analysis. In these cases, metaheuristic approaches arguably be a potential solution.

Chapter 4

Modelling of Feasible and Infeasible SCM cases

This chapter presents a list of feasible and infeasible SCM cases for several standard test networks. These cases will be used in later chapters to demonstrate the applicability of the proposed approaches.

4.1. Introduction

An overview of the SCM problem formulation and classification with relevant solution algorithms is discussed in previous chapters. It is mentioned that SCM cases can be divided into feasible (or manageable) and infeasible (or non-manageable) cases. Feasible cases are the cases for which there exists a corrective control solution that satisfies all constraints. Infeasible cases are the cases for which there exists no corrective control solution (with available/modelled controls) that can satisfy all constraints. Hence, the operator cannot devise a feasible generation dispatch and adjust available controls without violating at least one security constraint. It is also said that conventional optimization solvers are unable to both identify and solve the minimum intractable subsystem of constraints (MISC) that is the root cause for infeasibility.

Before dealing with infeasible models and identifying the MISC using the proposed framework, a set of feasible and infeasible SCM cases must be identified and validated. This chapter explains procedures to prepare and validate such feasible and infeasible SCM cases. While feasible cases can represent both unstressed and stressed operating conditions, infeasible cases represent only overstressed operating conditions.

4.2. Description of Analysed Networks

Five test networks are analysed in order to illustrate the proposed methodologies and demonstrate that the presented approaches can be scaled-up to larger systems. These networks are IEEE 14-bus (Figure 4.1), IEEE 30-bus (Figure 4.2), IEEE 39-bus (Figure 4.3), IEEE 57-bus (Figure 4.4), and UIUC 150-bus (Figure 4.5). While the basic details of the selected networks are shown in Table 4.1, complete information (bus and branch data, active and reactive capability limits, etc.) are adopted from [157, 191, 192]. Dynamic data, fuel cost coefficients and emission coefficients of different generation units are presented in Appendix A.

Table 4.1 Analysed Test Networks

Test Network	IEEE14	IEEE30	IEEE39	IEEE57	UIUC150
Number of Buses	14	30	39	57	150
Number of Generators	5	6	10	7	27
Number of Lines	15	35	34	63	157
Number of Transformers	5	6	12	17	60
Number of Fixed Shunts	1	2	0	3	3
Total Peak MW Demand	259	283.4	6097.1	1250.8	12679.89
Total Peak MVAr Demand	73.5	126.2	1409.5	336.4	3613.765
Maximum MW Capacity	655	435	7367	1975.88	23845.7
Maximum MVAr Capacity	(-52, 48)	(-102, 188,	(-160, 2807)	(-468, 699)	(-1772.03, 11022.53)

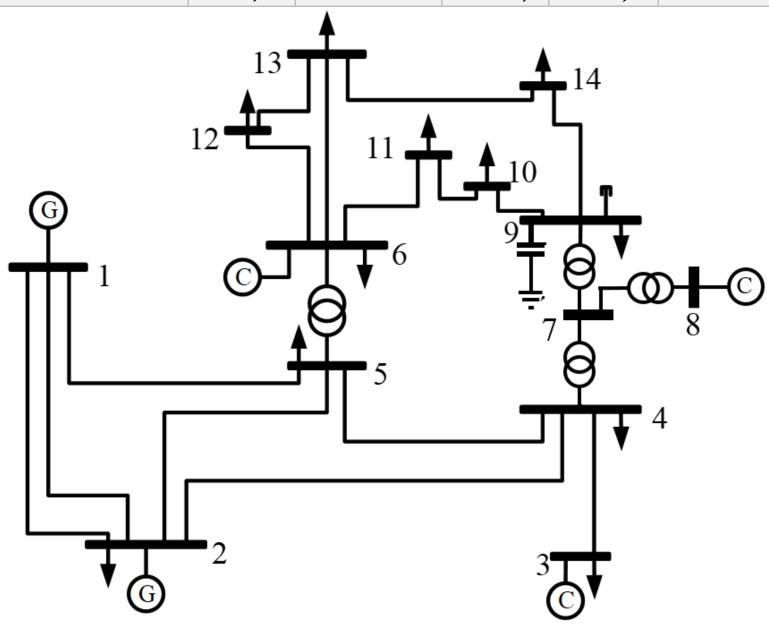


Figure 4.1 IEEE 14-bus Network [191]-[192]

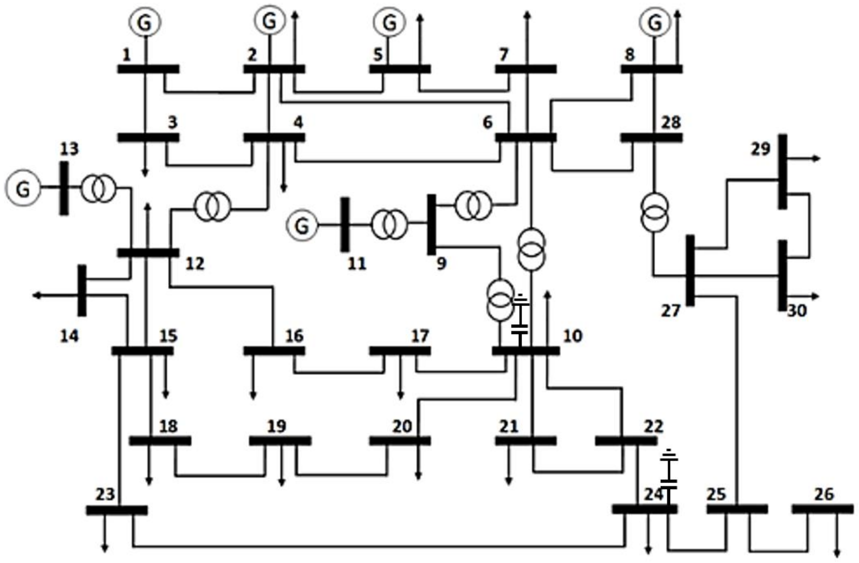


Figure 4.2 IEEE 30-bus Network [191]-[192]

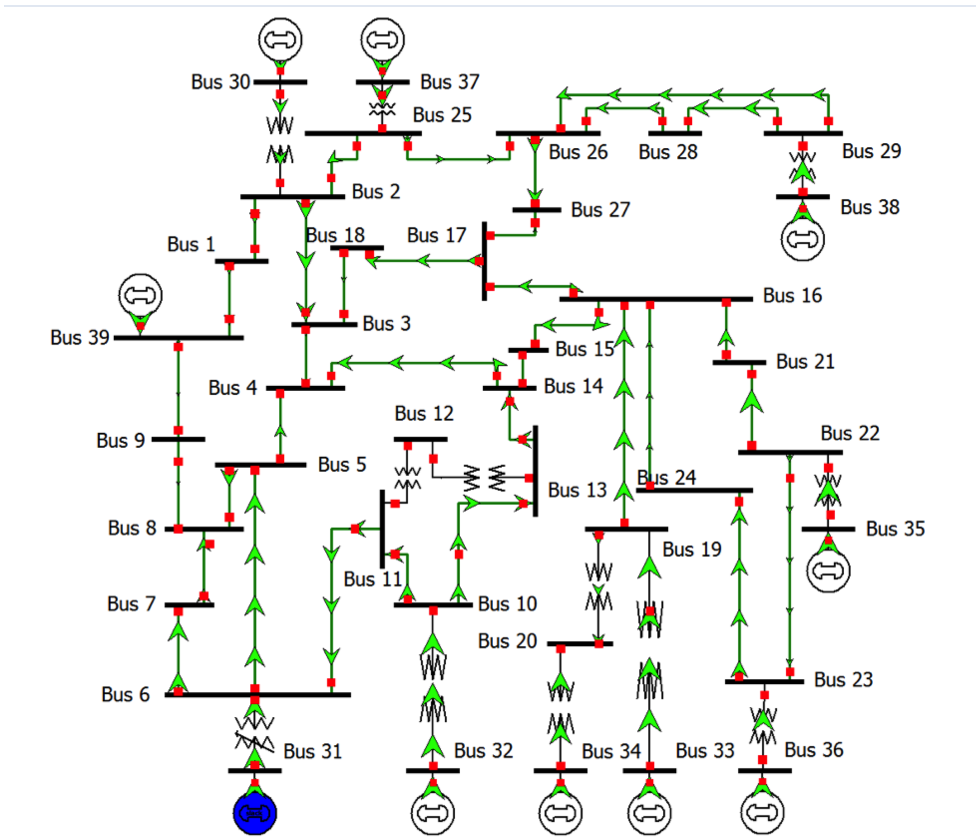


Figure 4.3 IEEE 39-bus Network [191]-[192]

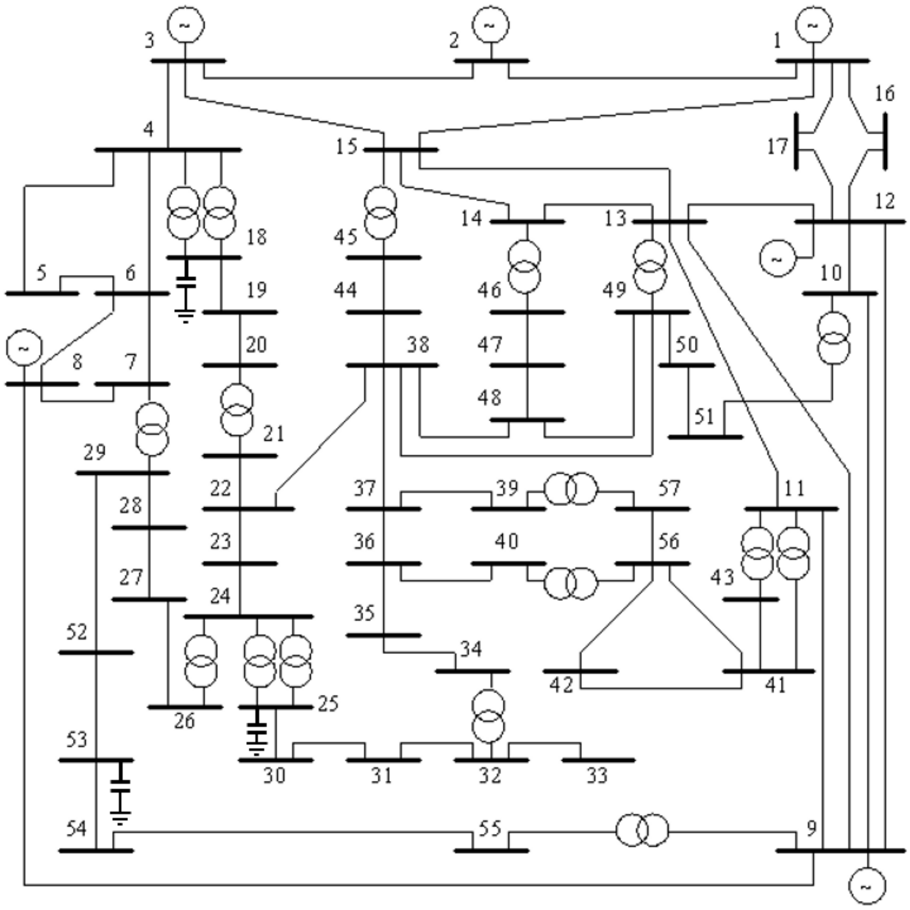


Figure 4.4 IEEE 57-bus Network [191]-[192]

It should be mentioned that these networks are analysed with their original characteristics and controls except in Chapter-7. In Chapter-7, extra controls (distributed generation, reactive compensation, controllable demand) are introduced as emergency control reserves. A framework is introduced in Chapter-7 to devise and implement remedial actions employing these emergency control reserves. The details of these emergency control reserves (type, locations, capacity, etc) are also discussed in Chapter-7.

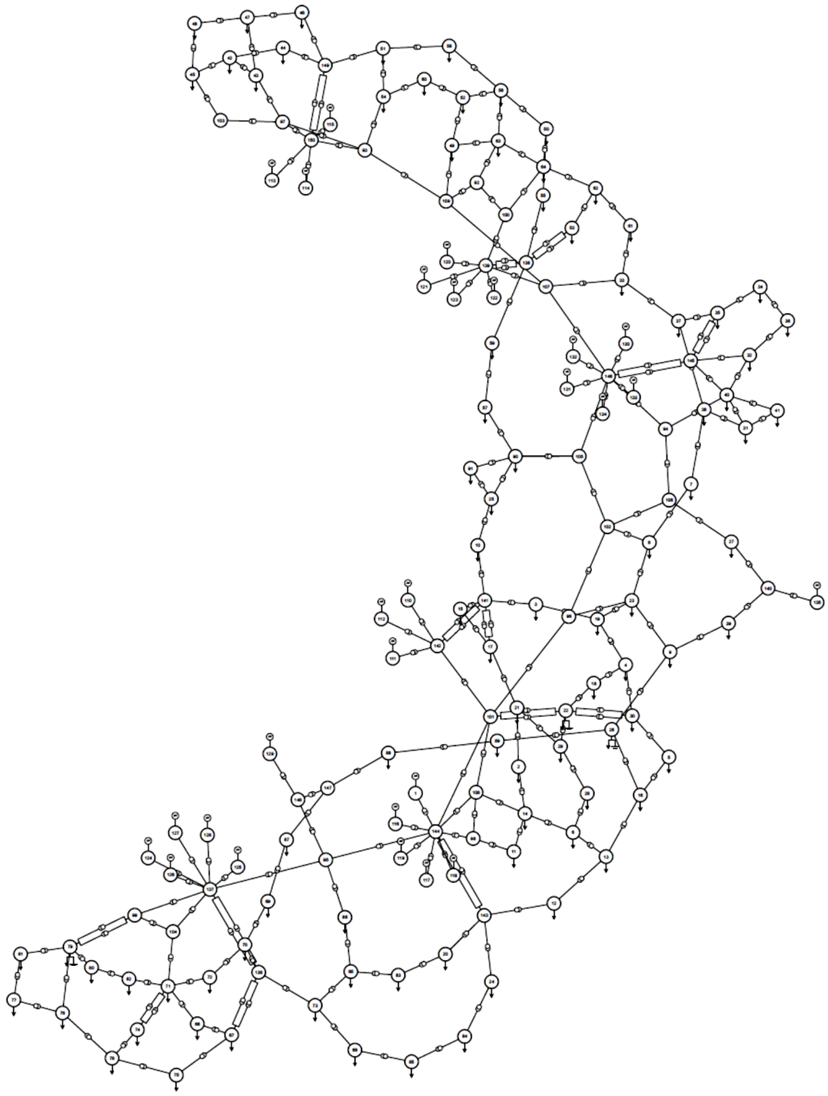


Figure 4.5 UIUC 150-bus Network [191]-[193]

4.3. Problem Settings

Several feasible and infeasible test cases are established by performing contingency analysis in PSS/E software [155]. The analysis settings used in the thesis are explained below. Unless stated otherwise, these are the default settings for the entire thesis.

SCM objective functions: SCM problem is solved mainly with two objective functions: a) fuel cost minimization (during non-overstressed operating conditions) and b) infeasibility minimization (during overstressed operating conditions). Only for pre-contingency analysis, SCM problem is also solved to minimize network losses and emission. The reason for doing this is to validate the custom-coded metaheuristic optimization solvers and compare their performance with conventional solvers.

Load modelling: System loads are initially modelled as constant power (CP) models, but constant current (CI) and constant impedance (CZ) models were also tried when conventional solvers failed to converge with CP model. The purpose of analysing with other load models is to relax demanded system powers and recheck the solver's judgement on model infeasibility.

Contingency analysis settings: The power mismatch tolerances are set as 0.01 MW and 0.01 MVAR for the base cases and 0.5 MW and 0.5 MVAR for the contingency cases [194].

Initial values: Pre-contingency operating conditions are inputted as initial values to the conventional solvers. If the solver does not converge with these pre-contingency operating conditions, flat voltage conditions are also tried, again to avoid the wrong judgement on infeasibility. However, initial values for metaheuristic solvers are always assigned randomly, as metaheuristic solvers are generally insensitive to initial values.

Optimization solver settings: In the analysis presented in this chapter, seven conventional OPF solvers (PSSE, IPAM, MIPS, FMINCON, PDIPM, SCPDIPM, TRALM) and three metaheuristic OPF solvers (GA, SA, PSO) are employed in order to develop stressed and overstressed operating conditions. All OPF solvers are executed on a 64-bit Intel® Core i7-3770, 3.4 GHz CPU desktop PC. The constraints in case of metaheuristic solvers are modelled with linear penalty functions (LPF, refer to chapter-3). Penalty factors for violating various constraints, and parameter settings for metaheuristic solvers are mentioned in Table 4.2.

Table 4.2 Parameter settings and penalties for GA, PSO and SA

GA settings	PSO settings	SA settings	Penalty settings
$\boldsymbol{N_{pop}}$=20	$\boldsymbol{N_{pop}}$: 20	$\boldsymbol{T_0}$=0.5	$\boldsymbol{p_q}$: 500
Selection: stochastic universal sampling	$\boldsymbol{C1 = C2 = 1.494}$	$\boldsymbol{t_r = 0.95}$	$\boldsymbol{p_p}$: 100
$\boldsymbol{p_c}$=0.8	$\boldsymbol{w = 0.729}$	-	$\boldsymbol{p_s}$: 100
Mutation: Gaussian	-	-	$\boldsymbol{p_v: 100}$

Where: N_{pop} – number of population or particles, p_c – crossover probability, $C1, C2$ – acceleration coefficients, w – inertia, T_0 – initial temperature, t_r – temperature reduction rate, $p_q, p_p,\ p_s\, p_v$ – penalty coefficients for reactive and active power, thermal and voltage violations.

4.4. Procedure for Modelling Feasible and Infeasible SCM Cases

Contingency analysis is employed to prepare feasible and infeasible instances of SCM problem. A contingency can happen for two main reasons: a) planned outage of system components, e.g. for maintenance and servicing purposes, b) unexpected outage of components, e.g. due to system faults or component failures. In general, most of the contingencies occur because of system faults and they are more severe than the planned outages, which are usually scheduled so there will be no contingencies.

Although utilities implement several preventive and corrective actions, to prevent the occurrence of contingencies and limit their impact if they occur, contingencies do happen and pose several problems during the operation. The severity of a contingency typically depends on the severity of the relevant fault. A set of SCM cases is developed by simulating non-severe and severe contingencies, and it is assumed that all the simulated contingencies are the consequences of system faults.

The detailed procedure is divided into the three following steps:

a) **Preparation of pre-contingency operating conditions:** As a base case, OPF problem with fuel cost minimization is formulated and solved for all considered networks, where computed pre-contingency control set points and operating point corresponding to this control solution is considered as a pre-contingency optimal operating condition for all considered networks, before simulating any contingency.
b) **Simulation and ranking of contingencies:** All possible double contingencies are simulated on pre-contingency network configurations (the first step) and immediate post-contingency (i.e. before activation of any corrective control) power flows and bus voltages are computed. Contingency cases are ranked based on the number of immediate post-contingency constraint violations.
c) **Selection of feasible and infeasible SCM cases:** High-ranked contingencies are resolved by adjusting available corrective controls to check whether the operator can devise a feasible dispatch, or not. PSS/E OPF solver is used to solve the

corrective control problem. The contingencies that can be resolved with available/primary corrective controls are considered as manageable or feasible SCM cases, because, following these contingencies, the operator can devise a feasible generation dispatch and adjustment of controls that can alleviate all active constraints. Although there are several such feasible cases for a given network, only one feasible case for each test network is selected for demonstration purposes.

The contingencies that cannot be resolved with any combination and adjustment of corrective controls are considered as non-manageable, or infeasible SCM cases. If these contingencies happen, it is impossible for the operator to devise a feasible dispatch that can alleviate all constraint violations, because no such solution exists. A network may have numerous infeasible configurations or contingencies that should be avoided. If these configurations happen, operator must implement remedial actions to preserve the integrity of the network. Two of such infeasible cases for each considered network are selected and analysed in this thesis.

4.5. Preparation of Pre-Contingency Conditions

Pre-contingency optimal operating conditions (e.g. generation dispatch) are computed by solving the base-case (BC) SCM/OPF problem with fuel cost as an objective function. Each base case SCM problem is solved 100 times by each solver and the maximum execution time of metaheuristic solvers is set to 8 min. While the minimum/optimal objective function value (i.e. fuel cost) over 100 runs is shown in Table 4.3, the corresponding generation dispatch is presented in Table 4.4 and Table 4.5. The results demonstrate that both conventional and metaheuristic solvers are returning almost similar generation schedule and fuel cost. The standard deviation of minimum objective values over 100 runs for each solver is also shown in Table 4.3. While conventional solvers can converge always to the same solution (indicated by zero standard deviation), metaheuristic solvers are converging to slightly different solutions (indicated by non-zero standard deviation), which is due to their stochastic nature, but, these standard deviations are very small.

The default operating condition of any test network is the pre-contingency optimal operating point, as it is optimal and n-1 (corrective) secure. All other operating conditions (e.g. overstressed conditions) and other instances of SCM problems (e.g.

feasible and infeasible problems) are developed by simulating non-severe or severe contingencies at these pre-contingency operating conditions.

Table 4.3 Optimal fuel cost ($/hr) found by various solvers

Solver	IEEE 14 (BC1)	IEEE 30 (BC2)	IEEE 39 (BC3)	IEEE 57 (BC4)	UIUC 150 (BC5)
PSSE	790.12/ 0.00	799.46/ 0.00	61990.00/ 0.00	41630.60/ 0.00	12780.10/ 0.00
IPAM	790.43/ 0.00	800.31/ 0.00	61990.04/ 0.00	41634.79/ 0.00	12780.56/ 0.00
MIPS	790.56/ 0.00	800.31/ 0.00	61990.04/ 0.00	41634.79/ 0.00	12780.56/ 0.00
Fmincon	790.56/ 0.00	800.31/ 0.00	61990.04/ 0.00	41634.79/ 0.00	12780.56/ 0.00
PDIPM	790.56/ 0.00	800.31/ 0.00	61990.04/ 0.00	41634.79/ 0.00	12780.56/ 0.00
SCPDIPM	790.56/ 0.00	800.31/ 0.00	61990.04/ 0.00	41634.79/ 0.00	12780.56/ 0.00
TRALM	790.56/ 0.00	800.34/ 0.00	61990.04/ 0.00	41634.79/ 0.00	12780.56/ 0.00
PSO	789.94/ 1.28	799.29/ 0.0003	61957.02/ 27.32	41631.14/ 11.59	12783.35/ 2.47
GA	790.25/ 1.30	799.29/ 0.0037	61960.18/ 31.70	41634.76/ 11.02	12781.07/ 1.27
SA	790.25/ 1.31	799.30/ 0.00576	61990.55/ 29.76	41635.01/ 19.17	12780.87/ 1.35

Table 4.4 Generation (MW) schedule at optimal fuel cost operation (IEEE 14 bus)

Solver name	Bus 1	Bus 2	Bus 3	Bus 6	Bus 8
PSSE	122.39	29.56	49.15	39.14	22.97
IPAM	122.55	29.63	49.41	39.80	21.79
MIPS	122.94	29.63	49.40	39.20	22.14
Fmincon	122.93	29.63	49.40	39.20	22.14
PDIPM	122.94	29.63	49.40	39.20	22.14
SCPDIPM	122.94	29.63	49.40	39.20	22.14
TRALM	122.94	29.63	49.39	39.20	22.14
PSO	121.73	30.30	49.26	39.01	22.78
GA	121.11	29.29	48.73	41.18	22.92
SA	122.23	29.47	49.13	38.97	23.32

Table 4.5 Generation (MW) schedule at optimal fuel cost operation (IEEE 30 bus)

Solver name	Bus 1	Bus 2	Bus 5	Bus 8	Bus 11	Bus 13
PSSE	177.06	48.67	21.32	21.2	11.87	12.01
IPAM	177.13	48.70	21.33	21.29	11.92	12.00
MIPS	177.13	48.70	21.33	21.29	11.92	12.01
Fmincon	177.13	48.70	21.33	21.29	11.92	12.00
PDIPM	177.13	48.70	21.33	21.29	11.92	12.01
SCPDIPM	177.13	48.70	21.33	21.29	11.92	12.00
TRALM	177.13	48.70	21.33	21.30	11.93	12.00
PSO	176.86	48.66	21.32	21.32	11.91	12.00
GA	176.86	48.64	21.32	21.37	11.89	12.00
SA	177.00	48.71	21.34	21.27	11.80	12.00

4.5.1 Validation of Metaheuristic Algorithms

Although the main objective of the formulated SCM problem is to minimize either fuel cost (during non-overstressed operating conditions), or infeasibility (during overstressed operating conditions), in this section, base-case SCM problem is also solved to minimize total network active power losses and emission. This is done to validate the performance of custom-coded metaheuristic solvers with respect to conventional solvers. Table 4.6 presents the optimal active losses and emission found by various solvers. Again, the results demonstrate that metaheuristic solvers most of the times provide solutions similar to conventional solvers, assuming that some minimum time is allowed for their search/analysis. No emission is calculated for 39, 57 and 150-bus due to unavailability of relevant emission data.

Table 4.6 Optimal Loss (MW) and Emission (ton/hr) found by various solvers (N-0)

Solver	IEEE 14		IEEE 30		IEEE 39	IEEE 57	UIUC 150
	Loss	Emission	Loss	Emission	Loss	Loss	Loss
PSSE	1.884	144.65	3.041	194.32	26.20	9.23	100.23
IPAM	1.195	144.58	3.138	194.29	26.30	9.41	100.64
MIPS	1.195	144.58	3.138	194.28	26.30	9.41	100.64
Fmincon	1.195	144.68	3.138	194.49	26.30	9.41	100.64
PDIPM	1.195	144.58	3.138	194.28	26.30	9.41	100.64
SCPDIPM	1.195	144.58	3.138	194.28	26.30	9.41	100.64
TRALM	1.360	182.11	3.192	203.43	31.45	10.14	100.65
PSO	1.240	144.58	3.180	194.26	26.21	9.59	102.16
GA	1.220	144.59	3.250	194.28	26.35	9.66	102.26
SA	1.230	144.59	3.100	194.32	26.35	9.55	102.66

4.5.2 Computational Performance of Used Solvers

While it is straightforward to calculate the average computational time required by a conventional solver to find the optimal objective value, it is very difficult to find a basis on which an average computational time can be calculated for metaheuristic algorithms. This is because of the existence of several convergence- and stopping-criteria for metaheuristic algorithms.

To overcome this problem and to compare the computational performance of metaheuristic solvers with conventional solvers, two time-performance indices for metaheuristic solvers are proposed.

a) Average time for finding the feasible solution (t_{feas}): This is the average time required by a metaheuristic solver to find a first feasible, but non-optimal solution over a given number of runs. Here, the basis for time calculation is feasibility.
b) Average time for finding the optimal solution (t_{opt}): This is the average time required by a metaheuristic solver to find an approximate optimal solution over a given number of runs. The approximate optimal solution is defined as an approximate optimal objective value which is either greater than 99.9% or less than 100.1% of the average optimal objective value achieved by a conventional solver. Here, the basis for time calculation is optimality.

While Table 4.7 shows the average computational time (over 100 runs) required by conventional solvers, Table 4.8 presents the average computational time required by metaheuristic solvers to achieve both feasibility and optimality again over 100 runs. The results demonstrate that metaheuristic solvers may require heavy computational time to find an optimal solution, but they require only up to a few tens of seconds to find the feasible solution.

Table 4.7 Average computational time(s) required by conventional solvers

Test Case	PSSE	IPAM	MIPS	Fmincon	PDIPM	SCPDIPM	TRALM
IEEE 14	0.038	0.916	0.055	0.069	0.017	0.021	0.049
IEEE 30	0.036	0.538	0.077	0.063	0.020	0.027	0.109
IEEE 39	0.081	1.403	0.142	0.108	0.029	0.039	0.238
IEEE 57	0.082	3.753	0.164	0.098	0.031	0.034	0.096
UIUC 150	0.085	47.874	1.883	0.153	0.090	0.136	0.365

Table 4.8 Metaheuristic solvers computational time (s, average)

Test Case	To find feasible solution (t_{feas})			To achieve approx. optimal solution (t_{opt})		
	PSO	GA	SA	PSO	GA	SA
IEEE 14	7.019	9.077	11.052	54.118	212.462	97.002
IEEE 30	1.847	3.942	5.923	18.816	72.329	63.531
IEEE 39	9.572	15.207	9.812	183.775	157.509	138.984
IEEE 57	7.220	25.441	38.067	57.125	120.356	118.851
UIUC 150	17.899	22.339	57.898	131.845	87.291	96.623
Aggregated Average (all networks)	8.7114	15.2012	24.5504	89.1358	129.9894	102.9982

Following observations can be drawn from the results in Table 4.3 to Table 4.8:

- For feasible cases, metaheuristic solvers can return almost the same objective value and generation schedule as conventional solvers. This confirms that the custom-coded metaheuristic solvers in this thesis are working in the way as they should be.
- Metaheuristic solvers are computationally inferior to conventional solvers, as they require hundreds (or even thousands) of function evaluations to find an optimal objective value. Metaheuristic solver's computational performance can be improved further in two ways: a) by parallelized implementation, and b) by implementing them in other efficient computer languages. For example, C++ compiler is at least 10 times faster than Matlab compiler.
- Metaheuristic solvers require heavy computational time to find the optimal solution, but they require only a few tens of seconds to find the feasible solution. This feature of metaheuristic solvers suggest they would be suitable for resolving infeasible SCM models.
- PSO outperforms over GA and SA in finding the best optimal objective value for 14, 30 and 57-bus networks. But GA performs better in case of 39 and 150-bus networks.
- Considering the aggregated average time required to find the feasible solution, PSO is computationally superior to GA and SA as it requires less time to find a feasible solution.
- Considering the aggregated average time required to find the optimal solution, PSO is computationally superior to other metaheuristic solvers.

- Considering heavy computational times, at this stage, it is difficult to advocate the benefits of metaheuristic solvers over conventional solvers, although both provide similar pre-contingency operating conditions.

4.6. Preparation of Feasible SCM Cases

A list of feasible SCM test cases, based on the procedure mentioned in Section 4.4, is developed by simulating a less severe contingencies (e.g. less severe faults, Table 4.9). After protection clears the fault, the system is analysed for constraint violations immediately after the contingency and before the application of any non-emergency corrective controls. This is carried out by solving an unconstrained power flow with pre-contingency (optimal) control set points applied on a post-contingency configured-network. In practical operations environment, immediate post-contingency constraint violations are monitored through the SCADA system. If any of the security constraints are active or violated, the next step is to mitigate these violations through available non-emergency corrective controls.

The number and type of immediate post-contingency constraint violations in the considered networks are shown in Table 4.9, with NUV and NOV standing for the number of under and overvoltage violations, while NOL stands for number of branch overloading violations.

Table 4.9 List of feasible SCM test cases with immediate post-contingency violations

Test Case	Network	Contingency Description	Immediate post-contingency constraint violations			
			NUV	NOV	NOL	Total
FC1	IEEE 14	L5-6 & L6-11	7	0	3	10
FC2	IEEE 30	L4-12&T6-9	0	0	3	3
FC3	IEEE 39	L10-13 & L16-24	3	0	3	6
FC4	IEEE 57	L3-4 & L8-9	29	0	8	37
FC5	UIUC 150	L88-89 & L107-146	0	7	5	12

4.7. Validation of Feasible SCM Cases

It is quite straightforward to prove the feasibility of an SCM formulation. Feasibility is confirmed, if there exists a corrective control solution that resolves all post-contingency constraints violations. In this context, following the contingency specified in Table 4.9, SCM problem is reformulated to include available (non-emergency) corrective controls and solved with several conventional and metaheuristic solvers. While Table 4.10 displays the convergence status of the employed solvers, Table 4.11 presents the corresponding optimal fuel cost to resolve all post-contingency constraint violations. The results demonstrate that all optimization solvers can converge and provide a feasible solution at which all post-contingency constraint violations are resolved. This confirms that the simulated feasible cases are indeed feasible.

Table 4.10 Convergence status of various solvers for feasible SCM cases

Test Case	PSSE	IPAM	MIPS	FMINCON	PDIPM	SCPDIPM	TRALM	PSO	GA	SA
FC1	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
FC2	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
FC3	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
FC4	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
FC5	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 4.11 Optimal fuel cost value returned by the solvers for feasible SCM cases

Solver	FC1	FC2	FC3	FC4	FC5
PSSE	886.23	809.42	62256.60	43063.30	12786.80
IPAM	892.93	813.31	62314.68	43296.48	12787.25
MIPS	872.67	811.21	62262.52	43097.99	12787.25
Fmincon	872.67	811.21	62262.52	43097.94	12787.26
PDIPM	872.67	811.21	62262.52	43097.99	12787.25
SCPDIPM	872.67	811.21	62262.52	43097.99	12787.25
TRALM	872.67	811.28	62262.52	43097.98	12789.99
PSO	868.06	809.22	62347.28	43086.58	12793.16
GA	865.31	809.23	62312.87	43064.76	12788.49
SA	868.68	809.51	62388.76	43088.56	12789.83

4.8. Preparation of Infeasible SCM Cases

A list of infeasible instances of SCM formulations (Table 4.12) is developed by deliberately simulating severe double line contingencies. The list of immediate post-contingency violations is calculated using the unconstrained power flow analysis, similar to feasible cases. These violations are shown in Table 4.12. If the operator tries to mitigate these overstressed operating conditions with only available non-emergency corrective controls, the resulting SCM formulations become infeasible (i.e. there is no solution with these controls that resolves all post-contingency constraint violations).

Table 4.12 List of Infeasible SCM cases with immediate post-contingency violations

Test Case	Network	Contingency	Immediate post-contingency constraint violations			
			NUV	NOV	NOL	Total
IC1	IEEE 14	L7-9&L6-13	0	0	4	4
IC2	IEEE 14	L5-6&L9-14	4	0	7	11
IC3	IEEE 30	L1-2 & T27-28	4	0	5	9
IC4	IEEE 30	L4-12 & T27-28	5	0	3	8
IC5	IEEE 39	L5-6 & L6-7	3	0	6	9
IC6	IEEE 39	L21-22 & L26-27	0	3	4	7
IC7	IEEE 57	T7-29 & L8-9	35	0	5	40
IC8	IEEE 57	T7-29 & L46-47	18	1	1	20
IC9	UIUC 150	T71-104 & L101-142	0	0	10	10
IC10	UIUC 150	L99-104 & L99-137	9	0	5	15

4.9. Validation of Infeasible SCM Cases

Verification of infeasibility is very important to avoid spending large computational times in solving infeasible SCM formulations. Once infeasibility is confirmed, the operator can concentrate on resolving infeasible SCM models to find the bottlenecks, or to locate the critical constraints causing infeasibility and to devise additional emergency controls to resolve them.

In this section, two indirect techniques are employed to validate the infeasibility of infeasible SCM formulations:

a) by solving the considered test cases with several conventional optimization solvers. Infeasibility is confirmed if more than two the conventional solvers either reports infeasibility, or fail to converge, as it is unlikely that more than two solvers will make a wrong judgement on problem infeasibility.
b) by checking the condition number of the Newton Jacobian matrix. In this way, the linear dependency of the gradients of the active inequality constraints against the gradients of equality constraints is checked over the iterations. Infeasibility is confirmed if the condition number of Newton Jacobian matrix is close to singular (e.g. monotonous increase in condition number over the iterations). This indicates the gradients of the active inequality constraints and gradients of equality constraints are linearly dependent on one another.

As part of the first technique, considered infeasible SCM formulations are solved with several conventional and metaheuristic optimization solvers. Table 5.3 presents the convergence status of these solvers. The results demonstrate that none of the conventional optimization solvers has converged, hence the considered cases are infeasible. To reinforce this judgement further, other information related to convergence process (e.g. 2-norm of the correction matrix, B) is extracted from one solver (PSSE) for one test case (Figure 4.6).

Table 4.13 Convergence status of optimization solvers for infeasible SCAM cases

Test Case	PSSE	IPAM	MIPS	FMINCON	PDIPM	SCPDIPM	TRALM	PSO	GA	SA
IC1	X	X	X	X	X	X	X	Y	Y	Y
IC2	X	X	X	X	X	X	X	Y	Y	Y
IC3	X	X	X	X	X	X	X	Y	Y	Y
IC4	X	X	X	X	X	X	X	Y	Y	Y
IC5	X	X	X	X	X	X	X	Y	Y	Y
IC6	X	X	X	X	X	X	X	Y	Y	Y
IC7	X	X	X	X	X	X	X	Y	Y	Y
IC8	X	X	X	X	X	X	X	Y	Y	Y
IC9	X	X	X	X	X	X	X	Y	Y	Y
IC10	X	X	X	X	X	X	X	Y	Y	Y

X-Indicates nonconvergence; Y-Indicates convergence to an infeasible point

As mentioned in Chapter 3, most of the conventional solvers utilize Newton-Raphson or similar equation solvers to solve the KKT conditions. As part of the implementation process, these equation solvers require to solve a linear system of the form $JX = B$. This system is usually denoted as Newton linear system, where J represents Newton Jacobian and B represents the correction matrix. Elements of the correction matrix drive the corrections in search (primal and dual) variables and the 2-norm of the correction matrix is typically calculated to quantify the correction. Zero value of the norm indicates no correction.

When solving feasible problems, the norm should reduce gradually and approach a negligible or a prespecified threshold value (indicating true solution). When solving infeasible problems, norm gradually increases with no-bound. The same phenomenon is demonstrated in Figure 4.6. PSSE even failed to converge with different combinations of load models (constant power, CP, constant impedance, CZ, constant current, CI) and initial values (pre-contingency optimal point, PC, and flat voltage point, FV). Infeasibility may be further verified with the monotonously increasing behaviour of power mismatch values below the prespecified threshold value.

Another indicator that manifests the infeasibility is the condition number of the Newton Jacobian matrix. The condition number for one feasible and one infeasible SCM case is extracted from MIPS solver and plotted in Figure 4.7. While the condition number is getting reduced or is not blowing-up over the iterations for the feasible case, the opposite phenomenon is happening while solving the infeasible problem, which indicates solver's failure to invert the Jacobian matrix.

While conventional algorithms did not converge for infeasible problems, metaheuristic algorithms can converge "at least" to an infeasible operating point. The number of constraint violations at this infeasible operating point might be much lower than the number of immediate post-contingency constraint violations. In some cases, the active constraints at the infeasible operating point provided by the metaheuristic solver may be the actual MISC that are causing infeasibility.

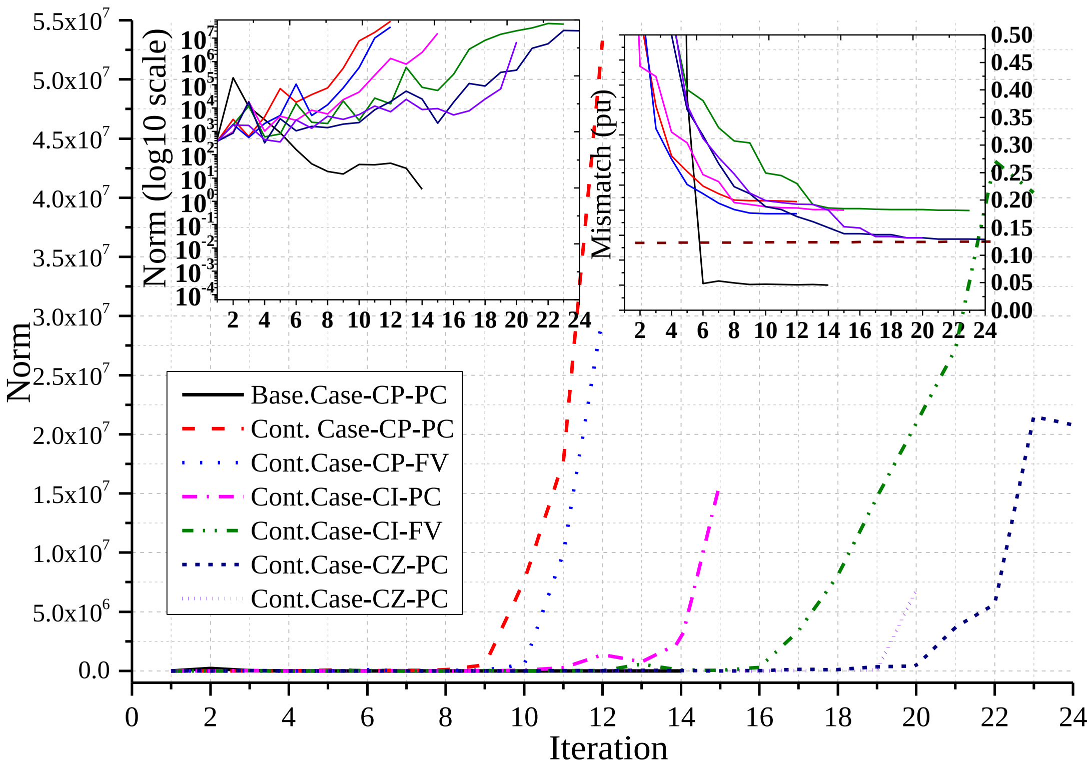


Figure 4.6 2-Norm of the correction matrix (BC2 and IC3)

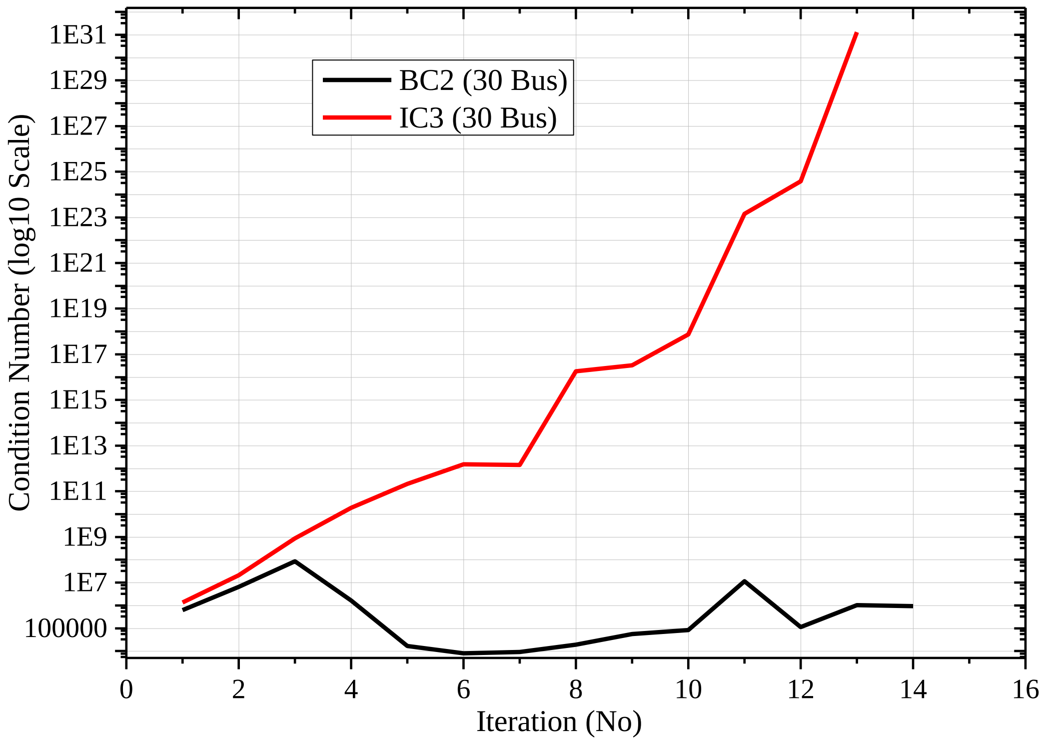


Figure 4.7 Condition Number of the Newton Jacobian (BC2 and IC3)

4.10. Conclusions

This chapter presented a set of feasible and infeasible SCM cases, which will be used in the next chapter to demonstrate the applicability of the proposed approaches for infeasibility diagnosis and resolution. Overstressed operating conditions, representing infeasible SCM cases, are developed by selecting and simulating severe contingencies. These overstressed conditions, for a given demand, also represent the infeasible network configurations as they might cause the system to lose stability and/or split into islands.

When the problem is feasible, both conventional and metaheuristic solvers can find a near optimal control solution that satisfies all constraints. When the problem is infeasible, conventional solvers will fail to converge, even to an infeasible control solution. However, metaheuristic solvers, although unable to find a completely feasible solution with available non-emergency controls, will converge to an infeasible operating point, at which the number of active constraint violations may be far lower than the number of immediate post contingency constraint violations. The active constraints at the infeasible operating point may or may not represent the actual MISC, or critical constraints, which will be discussed in depth in Chapter 5.

Finally, the information on critical constraints obtained from metaheuristic methods may be used by network planners and operators, either to aid the convergence process of conventional solvers, or to help with some other applications (e.g. management of system outages/faults, optimal load shedding, etc.). Chapter 7 is exclusively dedicated to discussing this aspect of the analysis, while the next chapter presents an infeasibility diagnosis and resolution framework to efficiently analyse and deal with the infeasible SCM cases developed in this chapter.

Chapter 5

Infeasibility Diagnosis and Resolution Framework

The chapter presents a modified metaheuristic approach and a framework based on this approach to localize and resolve infeasibility in nonlinear infeasible OPF/SCM problems.

5.1. Introduction

Optimal Power Flow (OPF) formulation remains to be one of the fundamental mathematical formulations for analysis of power systems, as almost all planning and operational problems can be analysed using this formulation. In general, SCM problems are also modelled with OPF formulation and typically solved with conventional optimization solvers (e.g. interior point solvers) [195]-[198]. While general OPF formulation focusses on minimizing various objective functions, SCM mainly focusses on minimizing either the severity (number and amount) of security constraint violations, or the cost of corrective actions to reduce the constraint violations. Hence, in this chapter, the terms OPF and SCM will be used interchangeably, while the literature review focuses on infeasible OPF formulations.

From the system operation viewpoint, OPF study aims to compute an optimal control solution to improve a system performance function (e.g. generation cost), while satisfying all security constraints. From an optimization viewpoint, OPF study involves finding an optimum solution to a set of nonlinear algebraic equations subjected to a set of equality and inequality constraints. Since its inception, most of the earlier research work has concentrated on developing computationally efficient mathematical formulations (i.e. to include complex objectives constraints, e.g. transient stability constrained OPF using metaheuristic solvers) and solution algorithms. However, very limited research work has been done to diagnose and resolve infeasibility when an SCM/OPF formulation actually becomes infeasible.

As discussed in Chapter 3, a nonlinear SCM formulation becomes infeasible due to the non-satisfiability of a minimal set of constraints, denoted as "*minimal intractable subsystem of constraints (MISC)*" in optimization theory [17]. A nonempty MISC lead to an empty (feasible) search space but an infeasible model can be made feasible either by removing, or relaxing MISC [17]. The SCM formulation aimed at solving a planning problem can be infeasible when the available resources cannot meet the given requirements. Similarly, SCM formulation aimed at solving an operational problem can be infeasible when available controls are insufficient to devise a feasible dispatch. This situation happens during the overstressed and emergency operating conditions (Chapter 4). Indeed, OPF becomes most valuable in these conditions, as the MISC can help operators to mitigate and resolve constraint violations [4].

It should be noted that none of the solvers can find a feasible solution to an infeasible SCM formulation, as such a feasible solution does not exist. The main point of the presented research is to establish a solver which can converge to a “most acceptable (or least severe) infeasible solution” in which all constraints, except these belonging to MISC, or these belonging to a somewhat bigger constraint set than MISC, are satisfied [4, 17]. When solving infeasible SCM formulations, conventional OPF solvers generally fail to converge and the information returned by the solver is of little use to locate the root causes of infeasibility (i.e. MISC) [4,17, 71]. However, being capable of performing random searches, metaheuristic solvers can converge to an acceptable infeasible solution and find the corresponding set of problematic constraints, which might not be necessarily equal to the MISC, but could be extremely useful to identify or estimate (and also locate) the MISC [10]. The main reason is that MISC is not known *a priori* and that there is currently no method or approach which can determine exact MISC for an infeasible OPF problem. Therefore, this thesis introduces an indirect MISC identification approach, where for a given infeasible model, the set of constraints reported as “problematic” by an optimization solver is denoted as “*problematic constraint set” (PCS)*. Depending on the size of identified PCS, MISC can be equal to PCS, or a subset of PCS.

However, the cardinality of the PCS to some extent depends on the performance of the implemented metaheuristic solver, where some solvers can find a PCS with a fewer members and others with more members, where former are obviously better than the latter. Moreover, even the same metaheuristic solver, if not implemented properly, can report different PCS’s in different runs. Hence, the lower and upper bound on the PCS’s are in this thesis denoted as *minimum likely size of PCS* (MinPCS) and *maximum* *likely size of PCS* (MaxPCS). A PCS can represent the actual MISC only when the intersection of MinPCS and MISC is equal, or very close to MISC (i.e. when their difference is an empty set). As mentioned, MISC cannot be known *a priori* and this can be verified only in an indirect way: MinPCS represents MISC if, and only if, the model becomes feasible by simultaneous relaxation or removal of all constraints in MinPCS. Even if one constraint in MinPCS is not relaxed or removed from the formulation, the model will be still infeasible (Section 3.3.4). This confirms that only the constraints in MinPCS are introducing infeasibility into the model.

The non-convergence of conventional OPF solvers due to problem infeasibility is a relatively common and less addressed computational issue in the open literature [3,4, 72]. Although OPF solvers based on linear models can more readily diagnose the infeasibility, there is no widely accepted or standardised methodology to identify the problematic constraints in nonlinear models [4]-[6]. As the results in this chapter show, the traditional soft constraint handling approach using various exterior penalty functions, as well as the constraint relaxation approaches, may not be successful in finding the MISC, or even MinPCS [10, 12]. The MISC, or its best representation by MinPCS, should be identified for two main reasons [73]: a) to find the minimum unfulfilled requirements to be relaxed, or to find the corresponding additional resources (minimum amount) for satisfying these constraints; and b) to find the minimum violated operational constraints to be relaxed, or to find locations where to activate emergency controls to mitigate the violated constraints.

In this context, this chapter presents an infeasibility diagnosis and resolution framework (IDRF), which first identifies the MinPCS as the closest representation of MISC by minimizing the infeasibility measures due to constraint violations, and then resolves infeasibility either by relaxing the related constraints, or by suitably penalizing the MISC. The IDRF focuses on the following problem: given an infeasible SCM formulation, how to identify the minimal set of constraints (i.e. MinPCS, or MISC) whose removal or relaxation would effectively isolate the infeasibility in the formulation?

Difference between PCS, MinPCS, MaxPCS, MISC and CCS

The definitions below are provided solely for the purpose of this PhD thesis. Furthermore, the presented work distinguishes between non-emergency corrective controls and emergency corrective controls, which are not available in immediate post-contingency state.

PCS: The set of constraints reported by an optimization solver at the minimized infeasibility measure, rather than for the original objective function of the problem.

MinPCS and MaxPCS: A metaheuristic optimization solver may not report the same PCS in every run, due to a stochastic nature of the search. In addition, the user may employ different solvers simultaneously to find the PCS. Assuming the range of possible variations in PCS size, the upper bound on PCS is considered as MaxPCS, while the lower bound is considered as MinPCS. However, if the user employs only one solver and executes that solver only once, the MinPCS and MaxPCS are both equal to the PCS reported in that single execution. In the presented analysis, the modified metaheuristic solvers can usually return the same PCS in most of the runs when the PCS found by the proposed metaheuristic solvers is equal to MinPCS.

MISC: For a given contingency case, resulting in overstressed system operating conditions, this is the absolute minimum set of constraints that makes the search space infeasible, or empty. The presented work assumes that MISC could be equal to a MinPCS, or that MinPCS is as close as possible, under the limitations of the applied metaheuristic solvers, representation of the MISC. The process of finding MISC is to identify the least possible number of constraints that cause the infeasibility, which is confirmed by the resolving of the infeasibility after these constraints are relaxed, or suitably penalised.

CCS: The minimum set of security constraints that prevents operator from devising a feasible dispatch for a given operating priority. The rest of the constraints are treated as noncritical.

While PCS, MinPCS, MaxPCS, and MISC are defined mainly for the purposes of diagnosing, identifying, localizing and resolving infeasibility from a “mathematical sense”, the CCS is defined to find the “bottlenecks” in the power system. While process of identifying PCS, MinPCS, MaxPCS, and MISC involves “minimization of infeasibility", the CCS identification process involves "optimization of given operator priority", e.g. minimization of the cost of corrective actions in post-contingency state.

Literature review: The problem of infeasibility in OPF models was previously addressed by some researchers and the majority of the research was carried out during the period 1980-2000. The existing literature can be classified into four areas.

a) **Approaches based on constraint handling** – this area of research focussed on handling the inequality constraints when the problem becomes infeasible. The developed approaches are: constraint relaxation [7, 48, 71, 74-80] and constraint penalization using linear and quadratic penalty functions [48, 71, 76, 79, 80]. While constraint relaxation approach enlarges the search space by expanding (i.e. relaxing) the constraint limits (e.g. increasing the line MVA limit to 150%), penalization accepts infeasible solutions with a given penalty. The main motivation behind these approaches is that only a minimum number of constraints will be violated at the final relaxed or penalized solution, which is not always true for nonlinear OPF problems. In conclusion, these approaches are mainly concentrated on infeasibility resolution, rather than on infeasibility diagnosis, because the number of constraint violations at the relaxed or penalized solution may be lower than the post-contingency violations, but they may not represent the actual minimum set of violated constraints (i.e. not MISC) in all cases.

b) **Approaches based on system controls** – this area of research mainly focussed on either adding or reducing the volume or number of controls to restore the feasibility. From mathematical sense, this is equivalent to increasing the limit of a specific variable in an equality constraint equation or adding more variables to an equality constraint equation. The main motivation behind these approaches is to identify the power deficit buses by increasing either the area or degree of control space. The volume of controls can be increased for some controls (e.g. limits of generators) and decreased for some other controls (e.g. load shedding). For example, the control space is enlarged by increasing the limits of generators beyond their rating in [48, 81], or by shedding the load in [48, 74, 75, 82]. The buses where the generation limits are violated, or the buses where load shedding takes place, are considered as power deficit buses and critical buses for infeasibility resolution. Infeasibility is restored by adding phantom or fictitious generators in [83].

Some authors added slack variables to both equality and inequality constraints and corresponding slack penalty values to the objective function to identify the active set of violated constraints in the final solution [84]-[86]. This approach, however, may not identify the key constraints causing the infeasibility when many slack variables are non-zero and might also impose difficulties in selecting the proper weighting factors to produce acceptable solutions. Again, these approaches mainly focus on non-restrictive (i.e. non-systematic) infeasibility resolution, rather than on methodological identification of the minimum number of constraints causing infeasibility, because the power deficit buses cannot help diagnosing the MISC. Power deficit buses indicate the buses at which energy imbalance takes place due to constraint violations, but they cannot say which constraint violations (voltage or thermal) causing that energy imbalance.

c) **Approaches based on algorithmic process modification –** this area of research has focussed on changing the standard process of optimization algorithms. The authors in [73] tried to resolve infeasibility in nonlinear OPF algorithms by defining threshold limit for each equality and inequality constraint, to identify a subset of active inequality constraints. During the iterations, the Lagrangian multiplier is fixed whenever it crosses the threshold, resulting in the relaxation of the corresponding constraint. This approach, however, needs careful selection of threshold values, as it may cause a feasible solution to become infeasible, or numerical instability of the algorithm [87]-[88]. Although the authors in [88] presented a systematic approach for selecting threshold values, the final solution may not be unique for different sets of initial values.
d) **Approaches based on fundamental optimization formulations –** this area of research has focussed on developing novel problem formulations to handle ill-posed and infeasible problems. For example, an alternative set of optimality conditions (Fritz-John conditions) is derived in [89] to solve OPF formulations with ill-posed feasible sets (i.e. not for infeasible sets). The main motivation behind this approach is that the standard KKT optimality conditions lead to an ill-conditioned Newton Jacobian matrix because of which the conventional solvers

will fail to converge, and the proposed Fritz-John conditions will resolve that issue. However, this approach has to be extended further, as it is not applicable to infeasible problems in general form.

In summary, most of the previous approaches effectively modify the original infeasible problem into a feasible one, rather than identifying the MISC, or at least MinPCS. In contrast, the proposed IDRF analyses the original infeasible problem in order to identify the MinPCS or MISC and then resolve infeasibility based on it.

The rest of the chapter is structured as follows: Section 5.2 presents the description and list of analysed overstressed SCM test cases. Section 5.3 demonstrates that the traditional infeasibility handling strategies cannot identify the MISC. Section 5.4 presents the modified metaheuristic approaches used in IDRF for identification of MinPCS that could represent MISC. Section 5.5 describes the proposed IDRF in more detail and Section 5.6 demonstrates the application of the IDRF on different test networks, illustrating main conclusions with the corresponding results.

5.2. Analysed Infeasible SCM Cases

Several infeasible test cases from Table 5.1 are used to demonstrate the proposed framework, which are the same test cases developed and validated in Chapter 4. These cases represent the selected overstressed operating conditions for the five test networks (IEEE 14, IEEE 30, IEEE 39, IEEE 57, and UIUC 150-bus networks). The aim of the IDRF is to find MinPCS from the immediate post-contingency total number of security constraint violations (TNSCV) and then evaluate how closely the MinPCS is representing MISC.

It should be noted that this chapter, if and as required, analyzes all or only some of the test cases listed in Table 5.1 to demonstrate the specific aspects of the IDRF framework. The main reason is to limit the attention and illustrate the main points of the approach proposed in this chapter.

Table 5.1 List of Analysed SCM Test Cases

Test Case: Contingencies	Network	NUV	NOV	NOL	TNSCV
IC1: T4-9&L6-13	IEEE 14	0	0	4	4
IC2:T5-6&L9-14	IEEE 14	4	0	7	11
IC3: L1-2 & T27-28	IEEE 30	4	0	5	9
IC4: L4-12 & T27-28	IEEE 30	5	0	3	8
IC5: L5-6 & L6-7	IEEE 39	3	0	6	9
IC6: L21-22 & L26-27	IEEE 39	0	3	4	7
IC7: T7-29 & L8-9	IEEE 57	35	0	5	40
IC8: T7-29 & L46-47	IEEE 57	18	1	1	20
IC9: T71-104 & L101-142	UIUC 150	0	0	10	10
IC10: L24-143 & L101-142	UIUC150	3	0	8	11

Note: Lx-y: Line between bus x and y; Tx-y: Transformer between bus x and y

5.3. OPF Infeasibility Diagnosis with Existing Approaches

This section implements the (common) traditional infeasibility handling approaches used by power system engineers (specific to OPF problem) and applied mathematicians (generally related to nonlinear optimization problems). The performance of these approaches is tested against several infeasible cases.

5.3.1 Approaches from OPF Community

Traditional approaches to infeasibility diagnosis in conventional solvers can be broadly classified into three groups, explained below.

5.3.1.1 Soft Penalization Approach (via exterior penalty functions)

This approach considers all constraints as soft, meaning that one or more constraints can be violated if they had to be. Every constraint is penalized for violating its limit and the aggregated penalty for all violations is added to the original objective function (as presented in Chapter 3). Hence, penalization approach replaces the original constrained optimization problem with an unconstrained problem, and repeatedly solves the problem until all (for feasible problems), or most of the constraints are satisfied (when problem remains infeasible). In general, the violated constraints at the final solution are considered as the problematic constraints, which are used to localize the infeasibility.

Conventional solvers basically use either linear penalty functions (LPF) or quadratic penalty functions (QPF) to implement this approach (Chapter 3). In LPF, constraint violation amount is multiplied by a penalty factor (K_p) and is added to the objective function. Similarly, squared violation, multiplied by a penalty factor, is added to the objective function in QPF. In further text, several infeasible cases are solved with a conventional solver (PSS/E) by implementing this approach. The list of resulting constraint violations at final solutions with various penalty factor (K_p) values is shown in Table 5.2.

Table 5.2 List of Problematic Constraints with Soft Penalization Approach

Test Case	LPF						QPF					
	Kp=10		Kp=100		Kp=1000		Kp=10		Kp=100		Kp=1000	
	NVV	NOLV	NVV	NOLV	NVV	NOLV	NVV	NOLV	NVV	NOLV	NVV	NOLV
IC1	5	4	0	4	0	4	14	4	0	4	0	4
IC2	11	4	4	4	4	3	14	4	14	3	2	4
IC3	13	3	5	2	3	2	24	2	7	2	5	2
IC4	9	2	5	2	4	2	23	2	5	2	5	2
IC5	20	3	5	3	13	3	11	1	X	X	X	X
IC6	39	2	16	3	8	1	14	1	X	X	X	X
IC7	57	2	33	1	27	1	57	1	23	1	X	X
IC8	57	0	26	0	10	0	57	0	57	0	31	0
IC9	32	0	48	4	18	0	21	1	X	X	X	X
IC10	23	2	13	2	14	2	X	X	X	X	X	X

NVV – number of voltage violations, NOLV – number of overload violations, X – non-converged

Conventional solvers can always converge to an infeasible solution with LPFs, but they still have convergence problems with QPFs. Generally, as the size of the modelled network and implemented penalty factors increase, conventional solver with QPFs will have smaller chance to converge (except IC8), even to an infeasible solution. This is because the quadratic penalty cost (i.e. the product of penalty factor and squared violation), for a given constraint violation, will be higher than the linear penalty cost, which forces the solver to find a feasible solution which does not exist. The higher the penalty cost, the higher the penalization pressure on the solver to find a feasible solution. Accordingly, LPFs are better than QPFs in solving infeasible problems.

The number of constraint violations at the final solution is significantly varying with different penalty functions and penalty factors. The violations decrease with increased penalty factor for IC1 to IC4. For other cases, the variations are not following any trend, or general rule. This indicates that conventional solvers are more sensitive to penalty factors.

For larger networks (IC7-IC10), the unconstrained solution seems far better than the penalized solution, because the numbers of constraint violations after soft penalisation are far higher than TNSCV. This indicates the severity of the contingency and the large shift in system operating point from the pre-contingency operating point. Probably, that is the reason why penalization is converging to a "local solution" (close to the pre-contingency operating point), which is inferior to unconstrained power flow solution.

It is also found that the conventional solver could report different sets of violated constraints (both in terms of numbers and indices, i.e., locations) with different initial conditions. This is obvious, because the solver usually converges to a local optimum, which is again close to the initial point. Nevertheless, the number of constraint violations in final solutions is still comparable to, or higher than TNSCV. In other words, it is clear that this approach is unable to locate/minimise the problematic constraints (MinPCS) properly, let alone to identify or correctly represent the MISC.

In conclusion, the traditional soft penalization approach (via exterior penalty functions) cannot help conventional solvers to diagnose the infeasibility in infeasible SCM problems (i.e. cannot reduce TNSCV to MinPCS).

5.3.1.2 Constraint Relaxation Approach

Constraint relaxation approach widens the search space by decreasing the lower bound and/or by increasing the upper bound of the violated constraints. It should be noted that constraint relaxation does not increase the dimensionality of the search space, which increases only when a new control function/parameter is added to the problem formulation. The main motivation behind the relaxation is to extend a feasible search space for the conventional solver to find the most optimal feasible solution (within this extended feasible search space), which is also assumed to be the most acceptable infeasible solution for the original infeasible problem.

In this section, all thermal branch MVA constraints are relaxed to 200% and the bus voltages are relaxed to range [0.8 1.2] pu. The selected infeasible problems are reformulated to include this relaxation and solved using a conventional solver (PSS/E).

Table 5.3 presents a list of problematic constraints with the constraint relaxation approach.

Unlike in soft penalization approach, the conventional solver can always converge to an infeasible solution with constraint relaxation approach. However, relaxation approach fails to reduce the number of identified problematic constraints to a lower value than TNSCV for most of the cases. The performance of the relaxation approach becomes much worse for larger networks. For example, the relaxed solution involves voltage violations across all the buses for case IC9 (150 bus network). One should remember that this solution is worse for the original infeasible problem, but it is a perfectly feasible solution for the relaxed problem. This indicates that the relaxation approach is more sensitive to the amount of relaxation and to the indices of relaxed constraints. However, it is very difficult to identify the list of the constraints to be relaxed and the relaxation amount, prior to the solution.

In conclusion, the constraint relaxation approach cannot help conventional solvers to diagnose or localise the infeasibility in nonlinear SCM formulations.

Table 5.3 List of Problematic Constraints with Relaxation Approach

Case	NVV	NOLV	Case	NVV	NOLV
IC1	7	2	IC6	20	3
IC2	7	5	IC7	26	2
IC3	13	4	IC8	25	0
IC4	13	3	IC9	150	3
IC5	20	5	IC10	147	1

5.3.2 Approaches from Optimization Community

While the OPF researchers focused on diagnosing infeasibility by minimizing original objective function (e.g. fuel cost or losses) plus the penalty cost for violating constraints (in a penalization approach), or by relaxing constrains outside of the physically possible bounds, optimization researchers focused on diagnosing infeasibility by minimizing the “infeasibility measures” (Section 3.3.5). From the optimization viewpoint, inclusion or exclusion of an objective function does not modify the search space of an infeasible problem, it just changes the way how search within it is performed. In other words, the objective function does not play significant role in deicing the infeasibility [1]. The main motivation behind minimizing the infeasibility measure is to minimize the active constraints to the least possible value (i.e. identify MISC, ideally) in the final solution. In optimization theory, a violated constraint in the final solution is denoted as an “active constraint”.

In this context, selected infeasible cases are reformulated to minimize the two infeasibility measures: the sum of infeasibilities, SINF (3.16) and the sum of squares of infeasibilities, SSINF (3.17). The reformulated problems are solved with conventional solver (PSS/E) and Table 5.4 presents the list of active constraints in the final solution.

The number of active constraints is not reduced significantly when compared to immediate post-contingency constraint violations. Indeed, the active constraints in the majority of cases are higher than the post-contingency violations, which is in contrast with a simple assumption that the size of MISC will be always lower than the number of post-contingency violations (TNSCV). Hence, seeing the increase of the number of active constraints, it is safe to say that the identified active constraints do not correctly, or even approximately represent the MISC (which is also demonstrated later in this chapter by showing reduction of the number of active constraints by the proposed approach). To sum up, the infeasibility minimization approach, similar to previously discussed approaches, cannot help conventional solvers to diagnose the infeasibility in nonlinear SCM problems.

Table 5.4 List of constraint violations with minimized infeasibility measure

	SINF		SSINF	
	NVV	NOLV	NVV	NOLV
IC1	0	3	0	2
IC2	0	7	1	7
IC3	7	5	25	5
IC4	5	4	5	3
IC5	23	2	27	1
IC6	15	4	39	4
IC7	12	3	40	0
IC8	12	0	37	0
IC9	5	7	22	0
IC10	9	5	9	3

SINF – sum of infeasibilities; SSINF – sum of squares of infeasibilities

5.4. Modified Metaheuristic Approach for IDRF

While most of the previous researches in metaheuristic optimization has focussed on developing algorithms for finding accurate optimal solutions to feasible optimization problems, solving (or "debugging") infeasible optimization problems with metaheuristic approaches is not yet explored. This chapter focuses on this unexplored field and employs metaheuristic optimization solvers to debug infeasible SCM problems and identify the MISC. In other words, metaheuristic solvers are employed to find the most acceptable infeasible solution to an infeasible problem.

Nevertheless, the existing metaheuristic approaches in their original form cannot be directly applied to infeasible problems, as they were mainly developed for solving feasible problems. Metaheuristic solvers require modifications to their search process to debug infeasible problems. For example, most PSO algorithms maintain high particle diversity during initial iterations (i.e. to favour exploration) and reduce diversity gradually (i.e. to favour exploitation around the optimum) to a minimum value. However, infeasible problems always require a high particle diversity to explore the new areas where constraint violations can be further reduced.

In this context, this chapter introduces three modifications (explained below) to the basic metaheuristic algorithmic framework, where the resulting approach is simply denoted as a "modified metaheuristic approach".

5.4.1 Novel Infeasibility Measure

The existing infeasibility measures (SINF, SSINF) are sensitive to scaling issues, and metaheuristic solvers do not perform well in minimizing these infeasibility measures in their original form. For example, a small violation of a thermal limit can be significantly higher (e.g. hundreds, or even thousands of times) than voltage limit violation, which causes an improper or non-uniform treatment of different violations caused by different constraints.

In order to facilitate the uniform treatment of all types of constraint violations and prevent the scaling issues in metaheuristic solvers, this chapter proposes a new infeasibility measure (denoted as the sum of the percentage of infeasibilities, SPINF, (5.2)) based on the calculation of the percentage of infeasibility, (5.1). As it is shown later in this chapter, metaheuristic optimization solvers can successfully search and find MinPCS that is lower than TNSCV by minimizing this infeasibility measure.

$$PINF_i = \begin{Bmatrix} \frac{x_{max} - x_i}{x_i} \\ 0 \end{Bmatrix} \begin{vmatrix} x_i > x_{max} \\ x_i < x_{max} \end{vmatrix} \tag{5.1}$$

$$SPINF = \sum_{i=1}^{N} PINF_i \tag{5.2}$$

5.4.2 Pre-conditioning of Decision Variables

In general, in almost all engineering optimization problems, the decision variables frequently fall under quite different ranges. In the case of the SCM problem, the control variables (e.g. voltage and active power generation) also falls in different ranges. These non-uniform ranges often result in a numerical ill-conditioning of underlying matrices (in case of conventional optimization solvers), or in an inefficient search (in case of metaheuristic optimization solvers), especially if search space is too narrow, or infeasible. In PSO, for example, the positions and velocities of the particles are updated by inertia, social and cognition coefficients and two random numbers to calculate the next position. As the variables lie in different ranges, the applied updates are non-uniform and particles might hit the boundary in one dimension, but not in the others. Similar description applies to other metaheuristic solvers as well.

To address this issue, all decision variables are transformed into a new space with the same lower and upper limits (0-100 in this thesis) using the linear transformation of variables. This pre-conditioning of decision variables resulted in improved computational performance and population diversity (in evolutionary algorithms), or particle diversity (in swarm intelligence algorithms) over the iterations [14].

5.4.3 Modified Personal Best Updating Criteria for PSO

The implemented PSO uses Newton Raphson Power Flow (NRPF) for evaluating solution of each particle. Traditionally, the particle's personal best is updated when it achieves an improvement in the fitness value, but as the algorithm is dealing with infeasible problems, there might be cases when the unconstrained power flow may not converge. Here, the non-convergence of the power flow is not because of insufficient generation in the system, rather it is because of the insufficient dispatch (although there is enough generation to meet demand) assigned to some particles by the PSO solver. These particles may be promoted to the next stage if they are not treated properly. To avoid this problem, the modified criteria require each particle to satisfy two conditions: a) new fitness value is better than the old one, and b) the power flow has converged.

5.5. Overview of Infeasibility Diagnosis and Resolution Framework

As mentioned, the objective function does not play main role in deciding the feasibility/infeasibility of a given optimization problem (in general), or SCM formulation (in particular). An SCM/OPF formulation becomes infeasible due to a non-satisfiability of typically a small set of constraints, denoted previously as the minimum intractable subsystem of constraints (MISC). Accordingly, the size of the MISC is practically always lower than the number of immediate post-contingency violations (TNSCV).

When a problem becomes infeasible, OPF solvers should provide the user with an information how intractable the problem is and what are the possible reasons for that, rather than simply returning a convergency failure message. In that case, an OPF program would be more valuable to the operator during these infeasible conditions, with an accurate or estimated MISC being very helpful in addressing the key constraint violations in a technically and economically efficient manner. Hence, identification or at least estimation of MISC is very important both from analytical and operational perspectives.

Existing commercial OPF solvers are not equipped with infeasibility diagnosis and resolution framework, so they cannot report anything related to MISC to the operator/user. This section presents a novel infeasibility diagnosis and resolution framework (IDRF) by employing the specifically modified metaheuristic solvers. Such a framework could be of significant help to network operators and engineers in handling challenging overstressed situations. By minimizing the modified infeasibility measure (SPINF), the IDRF tries to as closely as possible identify the MISC (from the mathematical interpretation of infeasibility), and then to resolve the infeasibility by either relaxing or penalizing constraints which represent the MISC.

5.5.1. Analytical Framework

The proposed IDRF is illustrated in Figure 5.1 and has the following four main stages:

1) *Loading of infeasible cases* – in this stage, the SCM problems that are believed to be infeasible by the operator are loaded to the IDRF framework.
2) *Verification of infeasibility* – this stage verifies whether the given SCM problem is infeasible or not. If infeasible, it proceeds to Stage-3; if feasible, it reports the feasibility status to the user and provides an optimal and feasible solution.
3) *Diagnosis of infeasibility* – if Stage-2 confirms the infeasibility, this stage identifies problematic/critical constraints which represents the MISC and report to it to Stage-4, as well as to the user.
4) *Resolution of infeasibility* – this stage resolves the infeasibility in the original formulation by relaxing or penalizing the constraints that represent the MISC and then it solves the reformulated problem and reports the solution, as well as the feasible version of the original problem to the user.

5.5.2. Loading of Infeasible SCM cases

In practical situations, the operator can forward the infeasible problems to the IDRF as and when they arise. However, for demonstration purposes, a set of infeasible cases in this section are loaded to the IDRF framework.

5.5.3. Verification of Infeasibility

This stage verifies the infeasibility of a given SCM problem by using two indirect techniques (Chapter 4): a) by trying to solve the given problem with several solvers in parallel, and b) by computing the condition number of Newton Jacobian matrix, J (3.38). Condition number is equal to the ratio of the largest to smallest singular value in the singular value decomposition of Newton Jacobian matrix (5.3). If all solvers fail to converge and condition number is monotonously increasing (e.g. greater than 10^8, [199]), IDRF confirms that the given problem is indeed infeasible and is inputted to the further diagnosis and resolution stages. If at least one solver solves the problem, the IDRF reports the feasibility status, as well as the feasible solution to the user.

$$k(J) = \frac{\sigma_{max}(J)}{\sigma_{min}(J)} \tag{5.3}$$

Where: J- Newton Jacobian matrix, σ_{max} – largest singular value of J, σ_{min} – smallest singular value of J, k – condition number of J

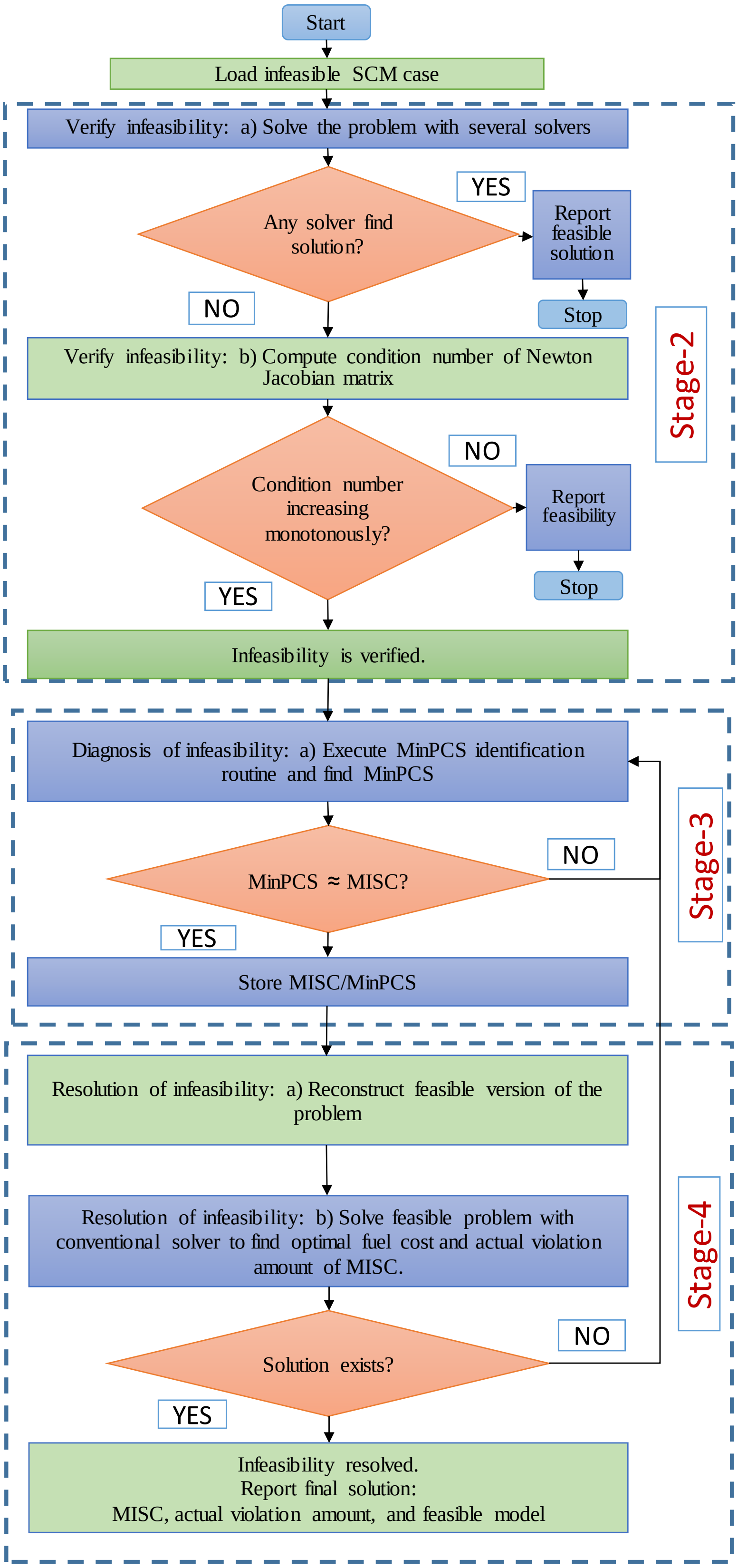


Figure 5.1 Metaheuristic Approach for MinPCS Identification

5.5.4. Diagnosis and Localization of Infeasibility

This stage debugs the confirmed infeasible problems with an aim to identify, or as closely as possible estimate the MISC. The problems reformulated by changing the objective function to proposed infeasibility measure, SPINF (5.2). The reformulated problems are solved with one of the solvers from the modified metaheuristic approach. However, all three solvers (PSO, GA, and SA) are implemented in this chapter to compare the performance of different solvers. The list of active constraints at the final solution is reported as minimum problematic constraint set (MinPCS).

A MinPCS can be characterised by three attributes mentioned below.

Cardinality, denoted as |MinPCS|: The cardinality of MinPCS is "the number of members of MinPCS", which are nothing else but the number of active/violated constraints in the solution corresponding to MinPCS. These constraints could be bus under and overvoltages and/or branch overloads.

Indices of active constraints denoted as IdxCV: These are the indices of violated constraints in the solution corresponding to MinPCS. Indices of violated constraints are nothing but the line numbers that are overloaded and/or bus numbers that are at under or overvoltage.

Infeasibility Measure, denoted as IM: This is the infeasibility measure (SPINF, (5.2)) calculated in the solution corresponding to MinPCS.

These attributes are used to compare several MinPCS that might be reported by different solvers. The one with the lowest cardinality and infeasibility measure is considered as the best amongst all MinPCS, i.e. the best representation of MISC, which might be the same as MISC. Accordingly, infeasibility diagnosis stage is further divided into two distinctive phases: a) *MinPCS identification phase* – in which infeasible cases are solved with metaheuristic solvers to identify all possible MinPCS's, b) *MISC estimation phase* – in which several MinPCS's are post-processed to find or estimate the MISC.

a) MinPCS Identification Phase

Figure 5.2 shows the main steps involved in MinPCS identification process. The search process of the metaheuristic solver is guided by the values of SPINF, rather than the gradients of constraints, as in conventional solvers. As the iterations progress, the guided stochastic search either leads to zero SPINF, or to the lowest found value of SPINF. If SPINF is zero, the problem is said to be feasible, otherwise, the problem is infeasible.

The constraints that contributed to nonzero SPINF in the best final solution from multiple runs are the most problematic constraints that are causing infeasibility. These constraints cannot be satisfied with modelled controls, and hence they are the most likely main causes of the problem infeasibility. However, this needs to be checked and verified. Hence, this phase reports these constraints as MinPCS to the MISC identification phase. It should be noted that MinPCS identification phase treats all constraints uniformly without any penalization. In other words, none of the constraints is modelled by penalty functions as the objective is to minimize the violation amount (i.e. SPINF). Hence, the sole purpose of minimizing SPINF is only to find MinPCS, purely from a mathematical viewpoint of infeasibility.

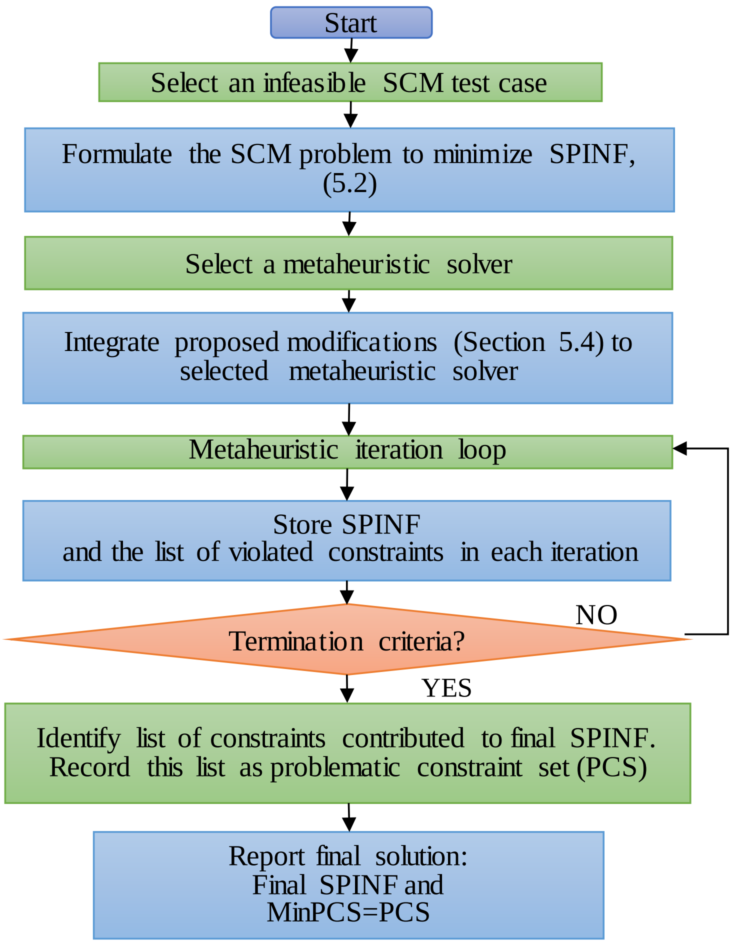


Figure 5.2 MinPCS Identification Process

b) MISC Estimation Process

This thesis assumes that MISC can be identified, or closely estimated by post-processing the active constraints in MinPCS. MinPCS and MISC are empty sets when the given optimization problem is feasible (i.e. all constraints are fulfilled), and non-empty sets when the given problem is infeasible (i.e. at least one constraint cannot be satisfied). For a given infeasible problem, MinPCS and MISC are equal if and only if their difference results in an empty set. In other words, the indices of active constraints and their violation amount are the same in both sets. This can be proved very easily, if the MISC is known *a priori*, e.g. from a hypothetical separate "MISC identifier", but in the context of the research presented in this thesis (and also elsewhere in the literature) such a MISC identifier is not available. Therefore, it is impossible to assess MISC's set equality with MinPCS. To overcome this problem, this thesis employs an indirect approach to prove that an identified "best MinPCS" can represent the MISC.

The indirect approach is motivated by the fact that "*an infeasible model can be made feasible by relaxing the constraints in MISC simultaneously*". If the simultaneous relaxation of all constraints in MinPCS also makes the model feasible, MinPCS can represent the actual MISC. In this context, the indirect approach reformulates the original infeasible problem by simultaneously relaxing all the constraints in MinPCS by the exact amount with which they are violated in the corresponding solution. The reformulated problem is solved again to minimize the infeasibility, SPINF. It should be noted that the reformulated problem is different from the original infeasible problem, as the bounds on problematic/critical constraints are changed. If there exists a solution with zero SPINF, it can be said that the MinPCS under test is best available representation of the MISC and it is therefore assumed to be equal to MISC.

$$\min f \tag{5.4}$$

$$s.to. \, g_i \leq 0 \tag{5.5}$$

$$PCS = \{g_i | i \in I\} \leq 0 \tag{5.6}$$

$$MinPCS = \{g_j | j \in J\} \; and \; J \subset \mathrm{I} \tag{5.7}$$

$$MISC = \{g_k | k \in K\} \; and \; K \subseteq \mathrm{J} \; \subset \mathrm{I} \tag{5.8}$$

If (5.4) – (5.5) is feasible:

$$|g_j| = 0 \rightarrow MinPCS = \emptyset \tag{5.9}$$

$$|g_k| = 0 \rightarrow MISC = \emptyset \tag{5.10}$$

If (5.4) – (5.5) is infeasible and if MinPCS represents MISC:

$$\rightarrow J = K$$

$$\rightarrow |g_j| = |g_k|$$

where:

f – objective function of the optimization problem (minimization of infeasibility measure); g – inequality constraints of the optimization problem

MinPCS – minimum most problematic constraint set representing most problematic constraints;

MISC – minimum intractable subsystem of constraints which are impossible to fulfil

I – set representing the indices of all constraints of the problem

J, K – sets representing the indices of active constraints in MinPCS and MISC

$|g_i|$ – amount of constraint violation of the i^{th} constraint

5.5.5. Resolution of Infeasibility

Ideally, when a model is infeasible, the user (e.g. network operator) wants to reconstruct a feasible model by relaxing as few constraints as possible and solve the problem with conventional solvers to compute the required amount of actual relaxation, or penalization. The user/operator can decide whether to ignore these constraints or incorporate additional resources (e.g. from available or contracted ancillary services) to fulfil these constraints based on the actual required relaxation or penalization values. Soft penalization and constraint relaxation are the two traditional and simplest approaches used to reconstruct a (mathematically) feasible model from the infeasible one, but these approaches typically require to relax or penalize larger number of constraints (as previously demonstrated). A better approach would be to build a feasible model by relaxing or penalizing only a minimum number of constraints (i.e. MISC, ideally).

In that context, this section presents such a methodology to resolve infeasibility and build a feasible SCM case, which can be later solved by the conventional solvers. The methodology is divided into *feasibility remodelling phase* and *solution phase*. In the *feasibility remodelling phase*, two feasible models, one by penalization and the other by the relaxation of constraints, are built from the original infeasible model. In practical situations, the user may be interested to reconstruct only one feasible model.

In the *solution phase*, these feasible models are solved using conventional solver to minimize the original objective function (e.g. fuel cost, as used in this thesis). Infeasibility resolution is confirmed, "*if and only if there exists a solution that satisfies all constraints as well as minimizes the objective function*".

5.6. IDRF Results

5.6.1 Loading of Infeasible Test Cases

The implementation and scalability of the proposed IDRF framework are demonstrated with several infeasible cases (Table 5.1). The main aim of the subsequent analysis is to verify their infeasibility and then to identify the MinPCS (or MISC, if possible).

5.6.2 Verification of Infeasibility

The selected infeasible cases were already tried with several conventional solvers in Chapter 4, where it is confirmed that all solvers failed to find a feasible solution. These results were shown in Table 4.13. Moreover, the condition number of the Newton Jacobian matrix, J (3.38), for all these cases is calculated here and shown in Figure 5.3. Monotonously increasing condition number confirms that the selected infeasible cases are indeed infeasible and are subjected to further processing in the next stage.

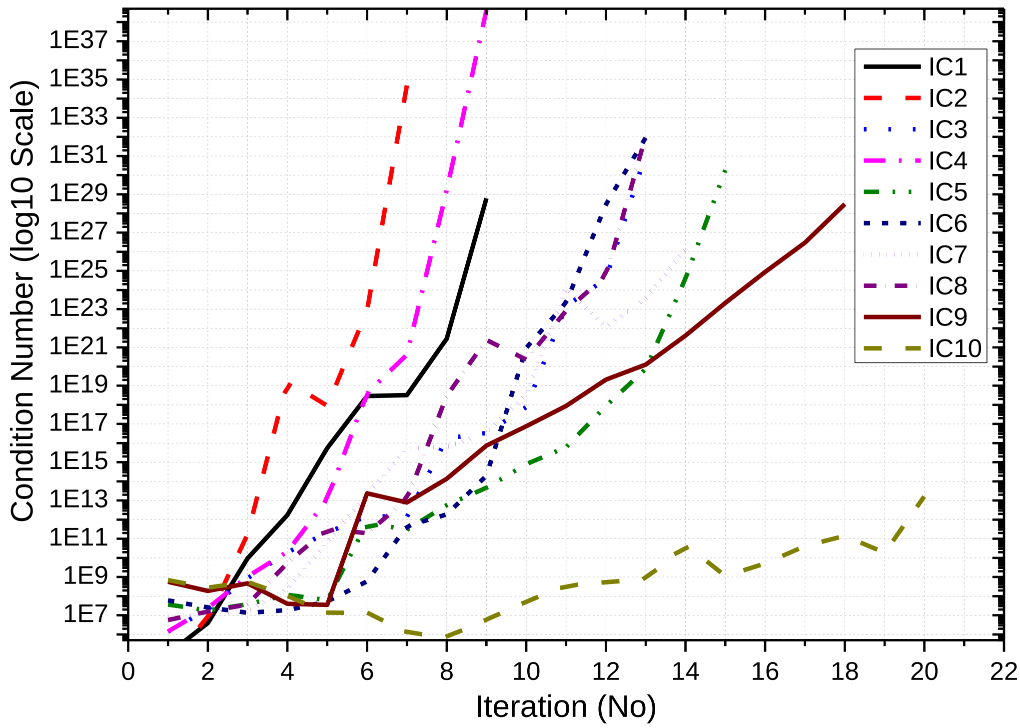


Figure 5.3 Condition Number of Newton Jacobian Matrix (IC1-IC10)

5.6.3 Identification of MinPCS

This stage employs three modified metaheuristic solvers to identify the set of best MinPCS's by minimizing SPINF as objective function (i.e. fitness function). However, in order to demonstrate the benefits of modified metaheuristic approach, infeasibility diagnosis is also carried out with traditional infeasibility measures (SINF and SSINF) and the non-modified metaheuristic solvers. While the solvers with the modified metaheuristic approach are denoted as MPSO, MGA and MSA in the results, the solvers with no modifications follows their original name (PSO, GA, SA). This notation is used only in this chapter just for the easy explanation of the results but in the remaining of this thesis modified metaheuristic solvers are used without letter "M" to their standard abbreviations.

It is worth mentioning that SINF, SSINF and SPINF are employed as objective or fitness functions for the considered modified metaheuristic solvers; and the target here is to minimize these objective functions. Each solver for each infeasible case is executed 50 times and the runtime of each execution is set to 5 min (solver terminates execution after 5 min). The maximum and the minimum number of constraints (MaxPCS and MinPCS) identified over 50 runs, the objective value or infeasibility measure (equivalent to SPINF), and the solver success rate to find MinPCS for minimized SINF, SSINF, and SPINF objectives are shown in Table 5.5, Table 5.6 and Table 5.7 respectively. For example, in case of the PSO for IC1 from Table 5.5, the results can be read as follows: PSO can find a solution with two violations 44 times out of 50 runs (i.e. 88% success rate) with the amount of violation equal to 59.70. In the remaining 6 times, it finds a solution with the number of violations greater than the MinPCS (i.e. two here), but less than or equal to MaxPCS.

The size of both MinPCS and MaxPCS is varying with the implemented solver and the minimized infeasibility measure. There is a large spread between MaxPCS and MinPCS for the minimized SINF and SSINF, when compared to the minimized SPINF. This is especially noticeable for larger networks (IC6-IC10). For example, the spread between MaxPCS and MinPCS for IC8 with SA is 29 for minimized SINF and 26 for minimized SSINF, while it is 4 for minimized SPINF. There are two reasons for this large spread: a) SINF and SSINF are sensitive to constraint scaling issues, b) basic metaheuristic solvers are unable to maintain good diversity between their search agents (i.e. particles, Figure 5.4). That is why modified solvers with SPINF are superior to the basic metaheuristic solvers with SINF and SSINF.

Table 5.5 MinPCS Identification with Minimized SINF

	MaxPCS			MinPCS			SINF (equivalent to SPINF)			Success rate (%)		
	PSO	GA	SA	PSO	GA	SA	PSO	GA	SA	PSO	GA	SA
IC1	3	3	3	2	2	2	59.70	59.70	60.90	88.0	86.0	8.0
IC2	1	1	1	1	1	1	36.38	36.38	36.38	100.0	100.0	100.0
IC3	7	7	7	7	7	7	47.10	47.33	47.50	100.0	100.0	100.0
IC4	6	6	6	6	7	6	74.02	74.00	74.00	100.0	68.0	100.0
IC5	11	8	6	4	4	2	54.43	59.01	51.74	8.0	12.0	26.0
IC6	7	20	4	1	1	1	42.43	42.28	43.04	72.0	56.0	76.0
IC7	19	23	17	6	6	6	27.99	26.36	32.44	32.0	52.0	12.0
IC8	38	17	35	11	6	9	42.88	27.03	13.65	10.0	22.0	14.0
IC9	10	22	20	2	12	13	24.42	39.35	50.69	72.0	10.0	12.0
IC10	3	3	5	3	3	3	11.88	11.75	12.28	100.0	100.0	90.0

Table 5.6 MinPCS Identification with Minimized SSINF

	MaxPCS			MinPCS			SSINF (equivalent to SPINF)			Success rate (%)		
	PSO	GA	SA	PSO	GA	SA	PSO	GA	SA	PSO	GA	SA
IC1	3	3	3	2	3	2	60.70	71.84	62.03	14.0	100.0	12.0
IC2	1	1	1	1	1	1	36.38	36.38	36.38	100.0	100.0	90.0
IC3	7	7	7	7	7	6	46.91	47.08	50.58	100.0	100.0	6.0
IC4	6	7	7	6	6	6	74.02	74.93	74.05	100.0	74.0	86.0
IC5	8	15	9	4	2	2	54.47	55.11	52.50	8.0	6.0	32.0
IC6	3	22	8	2	2	2	41.79	42.11	42.18	84.0	56.0	84.0
IC7	29	20	35	6	6	6	22.35	24.67	25.65	42.0	54.0	14.0
IC8	29	16	34	6	6	8	84.70	31.87	23.93	6.0	20.0	6.0
IC9	12	37	36	2	3	13	25.31	16.19	53.76	42.0	6.0	6.0
IC10	3	4	4	3	3	3	11.82	11.59	11.35	100.0	90.0	88.0

Table 5.7 MinPCS Identification with Minimized SPINF

	MaxPCS			MinPCS			SPINF			Success rate (%)		
	MPSO	MGA	MSA	MPSO	MGA	MSA	MPSO	MGA	MSA	MPSO	MGA	MSA
IC1	2	2	2	2	2	2	59.19	59.19	59.19	100	100	100
IC2	1	1	1	1	1	1	36.38	36.38	36.38	100	100	100
IC3	4	4	4	4	4	4	41.40	41.43	41.72	100	100	100
IC4	4	4	4	4	4	4	74.38	74.38	74.83	100	100	100
IC5	2	2	2	2	2	2	51.32	51.17	51.63	100	100	100
IC6	2	2	2	1	1	1	42.12	41.43	42.93	100	100	100
IC7	8	8	9	6	6	6	21.60	23.03	25.43	94	98	36
IC8	8	8	10	6	6	6	23.96	24.82	24.67	38	80	26
IC9	2	2	2	2	2	2	24.30	24.16	24.33	100	100	100
IC10	3	3	3	3	3	3	10.99	11.82	10.36	100	100	100

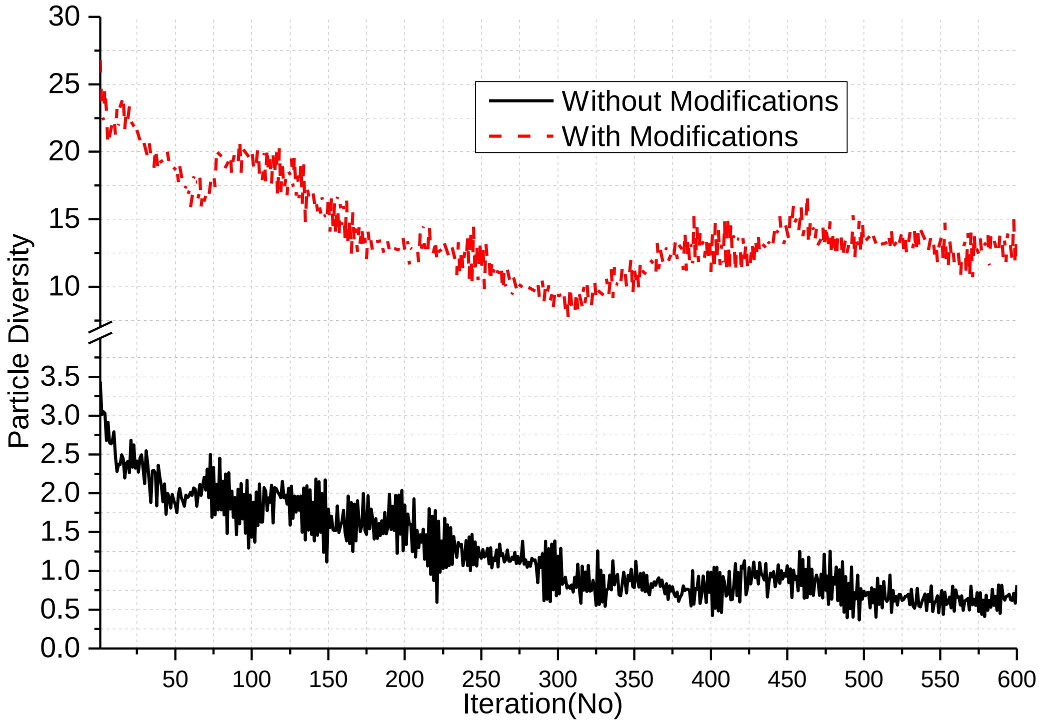


Figure 5.4 Particle diversity with proposed modifications to PSO

Modified solvers with minimized SPINF always find the best MinPCS (i.e. solution with the minimum number of violated constraints) in all cases, except IC7 and IC8. These cases are very severe, as they involve a large number of post-contingency constraint violations. The solvers have to perform an extensive search to find the solution with the lowest number of constraints (i.e. MinPCS equal to 6). That is the reason why the solver's success rate is lower than 100% for these cases for modified metaheuristic solvers. However, the success rate of the modified solvers is far better than the of basic solvers.

To compare the relative performance of the solvers, best MinPCS is selected from Table 5.5, Table 5.6 and Table 5.7. The best MinPCS is the one that has the lowest number of constraint violations and lowest infeasible measure (SINF, SSINF, SPINF). The solver's ability (i.e. success rate) to find the best MinPCS is listed in Table 5.8. The results demonstrate that modified solvers can always find the best MinPCS in all cases, while basic solvers fail to find the best MinPCS for the majority of these cases, with only a few examples of matched performance (most notably SA with SSINF). The performance of MPSO is superior to all other solvers, as it has the highest success rate for all the infeasible cases.

Table 5.8 Relative success rate of various solvers to find best MinPCS

		SINF			SSINF			SPINF		
	Best MinPCS	PSO	GA	SA	PSO	GA	SA	MPSO	MGA	MSA
IC1	2	86.0	8.0	14.0	0.0	12.0	100.0	100.0	100.0	86.0
IC2	1	100.0	100.0	100.0	100.0	90.0	100.0	100.0	100.0	100.0
IC3	4	0.0	0.0	0.0	0.0	0.0	100.0	100.0	100.0	0.0
IC4	4	0.0	0.0	0.0	0.0	0.0	100.0	100.0	100.0	0.0
IC5	2	0.0	26.0	0.0	6.0	32.0	100.0	100.0	100.0	0.0
IC6	1	56.0	76.0	84.0	56.0	84.0	100.0	100.0	100.0	56.0
IC7	6	52.0	12.0	42.0	54.0	14.0	94.0	98.0	36.0	52.0
IC8	6	22.0	0.0	6.0	20.0	0.0	38.0	80.0	26.0	22.0
IC9	2	0.0	0.0	42.0	0.0	0.0	100.0	100.0	100.0	0.0
IC10	3	100.0	90.0	100.0	90.0	88.0	100.0	100.0	100.0	100.0

Time performance (computational time) of modified metaheuristic solvers:

All solvers are executed on a 64-bit Intel® Core i7-3770, 3.4 GHz CPU desktop PC. While conventional solver (PSS/E) is implemented in C++ and FORTRAN, metaheuristic solvers are implemented in Matlab 2014a. The processor time (averaged over 50 runs) required to identify MinPCS is presented in Table 5.9. Even though conventional solver is executed substantially faster than the metaheuristic solvers, it is unable to provide a close representation of the MISC. Metaheuristic solvers, although requiring longer computational times, can find much better representation of the MISC in many of the cases. While metaheuristic solver's execution time varies with network size, the severity of infeasibility, and implemented penalty function, the average execution time is around 50 s.

Table 5.9 Execution Time (in seconds) Required by Various Solvers to Find MinPCS

Test Case	MPSO	MGA	MSA
IC1	5.775	16.75	19.525
IC2	4.575	9.725	27.4
IC3	33.65	37.175	62.075
IC4	45.325	101.275	60.4
IC5	26.7	40.2	25.625
IC6	20.975	43.925	39.95
IC7	48.325	91.875	135.6
IC8	75.875	186.225	99.95
IC9	27.725	26.6	43.675
IC10	79.15	53.325	63.025
Aggregated average	36.8075	60.7075	57.7225

Note: conventional solver's execution time is less than 0.5s

5.6.4 MISC Estimation

Postprocessing of MinPCS': In the previous section, several MinPCS' were identified using conventional and metaheuristic solvers by minimizing different infeasibility measures. It can be seen from the results that the cardinality and associated amount of infeasibility severity (measured/expressed by SINF, SSINF, or SPINF) of those MinPCS' could vary with the applied infeasibility measure and implemented solver. Only one of these MinPCS' should be now selected to represent the MISC and it is obvious that it is the one with the lowest cardinality and infeasibility measure. The one that fit this criterion is identified from Table 5.7 and its attributes are listed in Table 5.10. This MinPCS will be the target/best candidate for MISC. In practical situations, if the operator implements or employs only one solver, he will proceed with the results produced by only that solver.

Table 5.10 Best MinPCS under test

	No	Taken From	Indices of violated constraints	Violation Amount (absolute value from boundary)	SPINF
IC1	2	PSO	OL{15, 19}	OL{10.133, 3.302}	59.19
IC2	1	PSO	OL{20}	OL{4.365}	36.38
IC3	4	PSO	UV{29,30}; OL{33,35}	UV{0.022, 0.034}, OL{2.490, 3.199}	41.40
IC4	4	PSO	UV{29,30}; OL{33,35}	UV{0.013, 0.025}, OL{7.268, 3.170}	74.38
IC5	2	PSO	OL{3,9}	OL{95.822, 160.782}	51.32
IC6	1	GA	OL(3)	OL{207.148}	41.43
IC7	6	PSO	UV{24,27,28,29,52,53}	UV{0.010, 0.028, 0.044, 0.051, 0.042, 0.030}	21.60
IC8	6	PSO	UV{24,27,28,29,52,53}	UV{0.028, 0.038, 0.051, 0.056, 0.039, 0.024}	23.96
IC9	2	GA	OL{135, 137}	OL{78.888, 18.322}	24.16
IC10	3	SA	UV{24,84,85}	UV{0.047, 0.038, 0.014}	10.36

OL{k} – Overload at line k, OL{K}-Overload of K MW, UV{i} – undervoltage at bus i, UV{M} – undervoltage by M pu.

Testing of Target MinPCS: Target MinPCS will be tested if it can represent the MISC according to the criteria specified in Section 5.5.4. The original infeasible problems are reformulated by relaxing/expanding the constraints listed in MinPCS with the exact amount with which they were violated (Table 5.10). The reformulated problems are resolved with conventional and metaheuristic solvers with infeasibility measure as an objective function. It was observed that all conventional and metaheuristic solvers can converge and minimize the infeasibility measure to zero, which confirms that the MinPCS under test is indeed a (very) close representation of MISC, if not equal to it. To support this statement further, one conventional solver (PSS/E) is also tried by relaxing the different combinations of constraints in MinPCS with different relaxation amounts, rather than the actual amounts. In all these cases, conventional solver (PSS/E) failed to converge to zero SPINF, which supports previous conclusion about MinPCS' (suit)ability to represent MISC for a given problem.

5.6.5 Infeasibility Resolution

This stage reconstructs a feasible version of the original infeasible problem by one of the following two techniques:

a) ***Soft penalization of MISC***– in which a feasible model is built by treating only the constraints in the best MinPCS as soft constraints using linear (LPF) and quadratic (QPF) exterior penalty functions.
b) ***Constraint relaxation (CR) of MISC*** – in which a feasible model is built by relaxing only the constraints in MISC, with the exact amount with which they were violated.

In either case, the objective function is set back to the original objective function (i.e. fuel cost). These reconstructed problems are solved using a conventional solver (PSS/E) to minimize the original objective function (i.e. fuel cost, here). The solver's convergence status, optimal fuel cost, the actual amount of violation at the optimal solution are listed in Table 5.11. It should be noted that the violation amount is calculated against the original limits of the constraints in the best MinPCS and is converted to a SPINF equivalent value.

Table 5.11 shows that conventional solver (with penalty functions and constraint relaxation) can successfully solve all the reconstructed problems and converge to a (constrained) optimal feasible solution in which all constraints are satisfied. This confirms that the reconstructed problem is not infeasible anymore. More importantly, the presented analysis and introduced methodological framework is demonstrate that metaheuristic solvers can help convergence of the conventional solvers.

Table 5.11 Infeasibility Resolution Through Soft Penalization and Relaxation of the best MinPCS

Test Case	Converg. Status	Violation (equivalent of SPINF)				Objective Value		
		@MinPCS	@LPF	@QPF	@CR	@LPF	@QPF	@CR
IC1	✓	59.18	62.43	62.42	59.19	800.9	800.9	805.3
IC2	✓	36.38	36.63	36.64	36.38	823.3	823.3	825.1
IC3	✓	42.30	53.10	52.46	42.30	847.1	847.1	865.5
IC4	✓	74.37	99.07	101.40	74.37	810.3	810.2	824.2
IC5	✓	51.32	73.18	74.36	51.32	71112.0	71035.1	78104.1
IC6	✓	41.43	86.58	83.88	41.43	63792.9	64113.1	77159.9
IC7	✓	19.28	13.92	14.27	14.36	44870.7	44871.0	44870.8
IC8	✓	22.80	23.67	23.75	22.87	42333.4	42333.5	42333.7
IC9	✓	24.16	24.23	24.02	24.16	12823.9	12873.3	12832.6
IC10	✓	9.91	8.81	8.81	8.82	12799.7	12799.7	12802.8

The actual amount of constraint violation in the optimal solutions is varying with applied resolution techniques and it could be different from the best MinPCS violation, but not for much (it is almost equal). This is obvious, because constraint relaxation technique enlarges the search space by the specific amount and the solver is then able to find the solution within that search space, again confirming that the proposed IDRF can estimate or identify the MISC with the best MinPCS for a given infeasible SCM problem.

Relaxation-based infeasibility resolution technique is providing a solution with a bit lower violation amounts compared to LPF and QPF penalisation-based infeasibility resolution techniques. However, the solver (with constraint relaxation) can achieve this reduced violation only at the increased fuel cost (IC3-IC6).

While the constraint relaxation technique prohibits the solver to accept a solution outside the (modified) feasible boundary, soft penalization technique can allow the solver to accept a solution outside the (modified) feasible boundary. That is why the soft penalization technique can provide a reduced fuel cost solution, but at the expense of higher violation, and constraint relaxation technique can provide a reduced violation solution, but at the expense of higher fuel cost.

Once infeasibility is resolved, IDRF completes the execution process by reporting the following information to the user: MinPCS, constraint violation or relaxation amount for each constraint in MinPCS, and the feasible reconstructed model. Based on these data, the user can decide whether to ignore reported constraint(s) or mitigate them. The mitigation requires the user/operator to implement additional controls, which are not amongst the available corrective controls in immediate post-contingency state, but are activated as “emergency controls”, e.g. from the ancillary services, such as demand side management, transmission switching, load shedding, etc.

5.7. Conclusions

The OPF remains to be one of the most important mathematical formulations for planning, operation, and analysis (including market applications) of power supply systems. When dealing with infeasible OPF formulations, typically occurring due to severe contingencies resulting in overstressed operating conditions, the commercial OPF solvers fail to converge and return only a very limited information, which is very difficult to interpret by the engineers and operators. Essentially, the mathematical indication of infeasibility is related to practical physical conditions important for the secure system operation and any further attempt to operate the network under these conditions might result in system (angle and/or voltage) instability. When the system is overstressed, it is more important to as quickly as possible identify the root causes for the infeasibility (i.e. MISC), than to solve the OPF/SCM problem in its original or relaxed forms. Accordingly, there is an obvious need to incorporate an efficient and reliable infeasibility diagnosis and resolution frameworks or approaches into existing emergency controls (EMS) at energy control centres.

This chapter presented such as infeasibility diagnosis and resolution framework (IDRF) generally aimed at diagnosing and resolving infeasibility in nonlinear OPF/SCM formulations. The framework is built on a modified metaheuristic approach and a new infeasibility measure. The applied modifications are devised to improve the performance of the framework for finding the best possible representation of the MISC. The practical relevance of the framework is demonstrated with several infeasible SCM cases. It is expected that the presented framework could significantly help network operators and engineers in dealing with infeasible OPF/SCM problems, as and when they arise. The framework can be easily implemented as an additional functionality (or computational routine) in commercial OPF software, as the information on the MISC, or at least its close representation, can guide conventional solvers whenever they diverge, or fail to converge.

The various considered cases and corresponding sets of results indicate that the framework can reliably identify close/accurate representation of the MISC for the majority of the cases in less than 40 seconds on a standard desktop PC. Furthermore, the presented framework was implemented in MATLAB environment, and the computational performance can be improved by implementing it in C++ or FORTRAN, which are much faster (at least 10 times, [200]-[201]) than the MATLAB compiler. Computational time can be further reduced by exploring inherent task-level parallelism at objective function calculation stage and data-level parallelism at the optimization stage.

Without loss of generality, the framework can be easily extended to handle infeasibility in other optimization problems in power systems engineering (e.g. security constrained OPF and economic dispatch). The author is of opinion that the framework has significant potential for application in any field, as long as the problem involves a nonlinear optimization. For example, the framework can be extended to identify the critical alarms in process control centres (in process industries) during "*alarm flooding*" situations. The other example would the identification of cyber-attacks from the known system disturbances (see Chapter 8). Finally, although the present framework has implemented only three metaheuristic solvers, it is open to the researchers of similar interest to develop more efficient metaheuristic (or even conventional, if possible) solvers, integrate them into the framework and implement them in a suitable target application.

Chapter 6

Constraint Rationalization Framework for Overstressed Systems

This chapter presents a framework to rationalize the critical operating constraints based on various priorities of the operator to deal with overstressed operating conditions.

6.1. Introduction

An important prerequisite for the economic energy dispatch is fulfilment of the operational security constraints to retain the security and integrity of the network. Violation of any single constraint requires activation of proper corrective controls before protection trips other components. Chapter 4 showed that the violation of some security constraints is inevitable during overstressed conditions (e.g. following a severe contingency) as the operator cannot devise a feasible generation dispatch without implementing some emergency corrective control actions [43].

From system operations viewpoint, every constraint violation triggers an alarm, so the operator can notice the violation and take necessary action. If the number of alarms is low, an operator can rationalize the causes of their violations and implement most effective corrective actions optimally (e.g. at minimum cost), based on his previous experience. If the network experiences many constraint violations (e.g. more than ten), it will be extremely difficult for the operator to devise and implement effective corrective control actions, which are "optimal" from both technical and economic viewpoint. This situation, from process industries terminology, is called "alarm flooding" [90]-[91].

Therefore, it would be helpful for an operator to have a computational tool that can rationalize critical constraints, either based on the general control requirements, or specific operational priorities. Moreover, such a tool can guide the operator in finding the network "bottlenecks" or limiting factors that make power dispatch infeasible. Chapter 4 and Chapter 5 demonstrated that this situation can be modelled as an infeasible optimization problem, which has become infeasible due to a minimal set of constraint violations and will become feasible if these constraints are removed (or relaxed) from the problem formulation.

These minimal set of constraints are denoted as the minimal intractable subsystem of constraints (MISC) and Chapter 5 presented an infeasibility diagnosis and resolution framework (IDRF) to identify MISC from purely mathematical sense. In other words, IDRF rationalizes the constraints without paying any attention to control or operator priorities (e.g. costs of corrective controls, available emergency reserves, available time, etc.). When constraint rationalization is executed with operator priorities, the number and/or size (i.e. amount of violation) of the identified problematic constraints set might be different from the MISC. Accordingly, the most problematic constraints, from the operational sense, are denoted as critical constraints (CC) and corresponding set as the critical constraint set (CCS) in this chapter.

In this context, this chapter presents a metaheuristic constraint rationalization framework (CRF), which is capable of incorporating various operator priories. Accordingly, the presented framework rationalizes/filters the violated constraints into critical constraint set (CCS) and noncritical constraint set (NCCS), enabling the operator/user to execute the rationalization based on five operator priorities: cost of available non-emergency corrective actions, allocated available computational time, pre-specified size of CCS, available reserves, and available time before the next contingency occurs. Hence, the number and size of CCs in the corresponding CCS may vary based on the specific selected priority.

In modern electricity networks, the direction of generation to demand is changed due to increased penetration of distributed (typically renewable-based) generation and closing of the traditional thermal power plants, hence the power flows are also changed. The existing transmission lines were designed according to the original power flows (of that time) in order to cope with peak demand, but not peak times of renewable generation [92]. Hence, constraint management has become extremely important, as there is evidence that system operators spend millions of dollars every year on constraint management services [93]. The simplest and somewhat trivial solution to resolve constraint violations is to bring all the (non-emergency and/or emergency) reserves online wherever possible, but this solution would be infeasible either economically, or technically (e.g. ramping up times and further adverse dynamics during emergency conditions).

Most of the existing literature on constraint management has focussed on resolving constraint violations through various controls: distributed generation [94]-[95], FACTs devices [96]-[97], changes of network configuration [98], etc. However, a very few works focussed on identifying the critical constraints based on operator priorities and then use the locations and types of these constraints to devise optimal and most effective corrective actions. Moreover, majority of the previous approaches uses an optimization formulation (similar to OPF), but again a very few works (e.g. [81]) has focussed on analysing constraint management during the overstressed operating conditions, where these formulations become infeasible and some constraint violations cannot be resolved with non-emergency corrective controls. The authors in [28] divided the violated constraints into several controllable constraint groups (CCG) and then used constraint similarity and pattern recognition to identify the dominant constraint(s) in each group, suggesting that operator needs to take care of only these dominant constraints in each CCG. However, the application of CCGs and identification of dominant constraints for infeasible or overstressed conditions is not discussed.

A critical operating constraint forecasting (COCF) framework is proposed in [99] to predict constraints which can become critical in short-term (during the next hours). A set of linear equations (not ac power flow equations) are developed to estimate the changes in line power flows and bus voltages for a given daily load profile and/or operational scenario. Violated constraints are ranked, based on four different types of schemes, which are developed using the absolute or percentage violation of a constraint from its boundary value. The highest ranked constraints are considered critical. However, this framework does not discuss infeasible situations, in which the critical constraints may not be decided only based on the violation, but also on their prospect for resolution. This is because a constraint becomes critical only when the available corrective controls cannot resolve it. In overstressed or infeasible situations, a constraint with a lower “violation amount” (e.g. a line which is not with the highest overloading) can be more severe than the one with a higher “violation amount”.

To the best knowledge of the author of this thesis, the proposed framework (CRF) for identifying critical constraints during overstressed conditions based on operator priorities and infeasibility diagnosis is not reported previously, at least in the open literature.

The rest of the chapter is organized as follows: Section 6.2 presents the description and list of analysed overstressed SCM test cases. A dynamic penalty factor updating technique to enhance the performance of metaheuristic solvers is proposed in Section 6.3. Section 6.4 presents the generalized optimization formulation that is used as part of the proposed CRF. Section 6.5 presents an overview of the metaheuristic-based critical constraints identification process and presents the results to compare the performance of fixed and dynamic penalty factor techniques. Section 6.6 presents the analytical framework and demonstrates the applications of the framework with results on different test networks.

6.2. Analysed SCM Test Cases with Overstressed Operating Conditions

Several infeasible test cases from Table 6.1 are used to demonstrate the proposed framework. These are the same test cases which were developed and validated in Chapter 4 (Table 4.3), representing the selected overstressed operating conditions for the five test networks (IEEE 14, IEEE 30, IEEE 39, IEEE 57, and UIUC 150-bus networks). The list of immediate post-contingency constraint violations and the pre-contingency fuel cost for these networks is also shown in Table 6.1, where NUV, NOV and NOL indicate the number of bus undervoltage and overvoltage violations, and line overloads, respectively, while TNSCV indicates the total number of security constraint violations. It should be noted that this chapter, if and as required, analyzes all or only some of the test cases (listed in Table 6.1) to demonstrate the specific aspects of the constraint rationalization framework. The main reason is to limit the attention and illustrate the main points of the approaches proposed in this chapter.

Table 6.1 List of Analysed SCM Test Cases with Immediate Post-Contingency Constraint Violations

Test Case	Network	NUV	NOV	NOL	TNSCV	Pre-contingency Fuel Cost ($/hr)
IC1: L4-9&L6-13	IEEE 14	0	0	4	4	790.38
IC2:L5-6&L9-14	IEEE 14	4	0	7	11	
IC3: L1-2 & T27-28	IEEE 30	4	0	5	9	799.92
IC4: L4-12 & T27-28	IEEE 30	5	0	3	8	
IC5: L5-6 & L6-7	IEEE 39	3	0	6	9	61983.80
IC6: L21-22 & L26-27	IEEE 39	0	3	4	7	
IC7: T7-29 & L8-9	IEEE 57	35	0	5	40	41634.03
IC8: T7-29 & L46-47	IEEE 57	18	1	1	20	
IC9: T71-104 & L101-142	UIUC 150	0	0	10	10	12780.88
IC10: L24-143 & L101-142	UIUC150	3	0	8	11	

Note: Lx-y: Line between bus x and bus y; Tx-y: Transformer between bus x and y

6.3. Dynamic Penalty Factor Updating Technique

When constraints are modelled using penalty functions, penalty factors significantly influence the performance of the associated solver of any type. Like the conventional solvers, metaheuristic solvers also need careful tuning of penalty factors, as otherwise search can be driven into an infeasible region. In most of the earlier literature, these penalty factors are fixed and mainly applicable to feasible optimization problems. However, if penalty factors are changed, this will allow to "modulate" the constraint penalization "pressure", and in that way direct the search to the locations in system sate space where more constraints will be satisfied. To illustrate that, a novel *dynamic penalty factor updating technique* (6.1) is presented in this section, which requires setting of only the initial values (K_h). The penalty factor values are then automatically updated over the iterations, based on the actual number of constraint violations.

Initial penalty factor values (Table 6.2) should be selected based on the priority of the constraints. In this thesis, the violation of reactive power generation is considered as more severe than the violations of voltage and thermal limits. All penalty factor values should be at least in the order 100's, so a change in objective function with respect to a change in constraint violation can be identified and then used to guide the search. It is exactly this sensitivity to the constraint violations that helps metaheuristic solvers to minimize the number of constraint violations. In other words, dynamic penalty factor updating method helps mimicking the nature of gradient sensitivity with respect to iteration-based number of constraint violations, as in the conventional algorithms.

$$K_h^{Itr} = K_h^{NCV(Itr)} \tag{6.1}$$

Where: K_h- initial penalty factor value for violating a specific constraint in $h(x)$ (Table *6.2*), K_h^{Itr} - penalty factor for violating a specific constraint at iteration Itr, NCV - number of constraint violations in specific constraint group at iteration Itr.

Table 6.2 Initial Penalty Factor Values

Reactive Power ($\boldsymbol{p_q}$)	Active Power ($\boldsymbol{p_p}$)	Branch Thermal Limit ($\boldsymbol{p_s}$)	Bus Voltage Limit ($\boldsymbol{p_v}$)
500	100	100	100

6.4. Generalized Problem Formulation for CRF

CRF framework considers five types of operator priorities: i) cost of available non-emergency corrective actions (CANECC), ii) available or allocated computational time, iii) pre-specified number of critical constraints in the target set, iv) types and locations of available emergency reserves, and v) lead-time available to the operator before the next contingency occur. While priorities ii, iii, iv are modelled as solver termination criteria, the remaining priorities are modelled as the objective function.

The generalized optimization formulation used in the CRF are expressed by (6.2) - (6.5). Unless otherwise stated, the objective function for the four priorities is the cost of available non-emergency corrective actions (generation re-dispatch, AVR setpoint, tap setting adjustment, reactive compensation, etc.). Here, cost of available non-emergency corrective actions (CANECC) is considered as the difference between the pre-contingency fuel cost and post-contingency fuel cost with (non-emergency) corrective actions, assuming the operator's default priority is to reduce this cost.

$$min\ f \tag{6.2}$$

$$s.t.\quad g = 0\ and\ h \leq 0 \tag{6.3}$$

$$\rightarrow min\ F \tag{6.4}$$

$$F = f + K * \emptyset(\ g, h) \tag{6.5}$$

$$CANECC = FC_{post,c} - FC_{pre,c} \tag{6.6}$$

Where: f – original objective function (OOF), F – penalized objective function (POF), g, h - equality (3.2) and inequality constraints (3.3), $\emptyset$ - penalty function for modelling constraint violations, K – penalty factor (6.1), $FC_{pre,c}$ – pre-contingency fuel cost, $FC_{post,c}$ – post-contingency fuel cost with corrective actions.

Regarding the penalization, Log barrier penalty function (BPF) from the interior penalty function category and step (SPF), linear (LPF) and quadratic penalty functions (QPF) from the exterior penalty functions category are implemented to penalize the constraint violations. The penalty factor values are dynamically changed using the dynamic penalty factor updating technique. The original objective function (OOF) can represent the CANECC or lead-time available for handling the next contingency (this is discussed in Sub-section 6.6.5.5).

6.5. Critical Constraint Identification Process

The flowchart in Figure 6.1 explains the steps involved in identifying the critical constraints using metaheuristic solvers. The overall search process is guided by the values of the penalized objective function (POF), rather than the gradients of POF. The POF is the summation of the original objective function (OOF) plus the penalty cost (PC) for violating the constraints, (6.5). The solver search process can be divided into two phases: a) PC minimization phase – in which PC dominates over OOF and hence the search entirely focusses on minimizing the PC until there are no further PC changes, and b) OOF minimization phase – in which OOF dominates over PC, or there will be no further change in PC, hence the search focusses on minimizing OOF until there will be no change in it.

In general case, the solver will shift between these two phases based on the nature of stochastic solutions generated during the search process (Figure 6.2). While the variable scaling technique (Section 5.2.2) always maintain a diversity in the stochastic solutions, dynamic penalty factor technique always tries to introduce a change in the POF until no further reduction is possible. Hence, metaheuristic solvers can guide their search to locations in the search space where only minimum number of constraints are violated.

Solver keeps track of the PC (i.e. the difference between POF and OOF), which indicates the list of constraints that are violated in a given iteration. Zero PC means no constraint violation. The remaining constraints in the final PC are the denoted as the “critical constraints” because, for a given network configuration and demand, and for a given operator priority, these constraints cannot be satisfied with the existing non-emergency corrective controls.

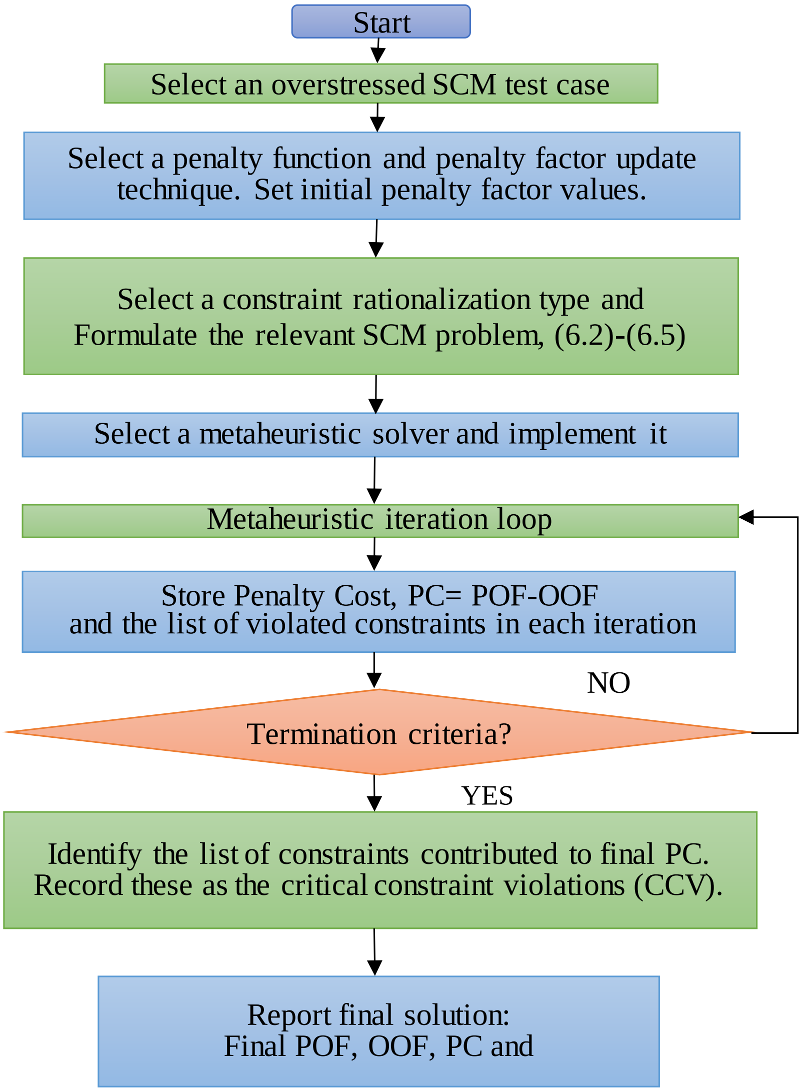


Figure 6.1 Critical Constraint Identification Process

6.5.1 Comparison of Fixed and Dynamic Penalty Factor Techniques

The performance of dynamic penalty factor technique (DynPF) and fixed penalty factor technique (FixPF) are compared for one infeasible SCM case (IC1). Three metaheuristic solvers (PSO, GA, and SA) with four different penalty functions (BPF, SPF, LPF, QPF) are employed to analyse the selected infeasible test case.

Each solver with different combinations of penalty functions and penalty factor updating techniques is executed in 50 runs, each with up to 600 iterations, and the results are shown in Table 6.3. MinNCC and MaxNCC represent the minimum and the maximum number of critical constraints identified by each solver over all 50 runs. The success rate of the solver, for a given penalty function and penalty factor technique, indicates the probability of finding the most minimum number of critical constraints (i.e. the minimum of all MinNCCs). Solver's average time, for a given penalty function and penalty factor technique, indicates the average time taken by the solver to identify its own MinNCC. In addition, the post-contingency fuel cost is also shown for every possible case. The results clearly indicate that the dynamic penalty factor updating technique is performing better in all the respects when compared to fixed penalty factor updating technique. The variations in the penalized and original objective functions (here fuel cost), and the number of constraint violations over the iterations is plotted in Figure 6.2 for one test case (IC3).

Table 6.3 Comparison of Fixed and Dynamic Penalty Factor Methods (IC1)

Penalty function	Solver	MaxNCC		MinNCC		Success Rate (%) (min (MinNCC))		Avg. time (s) (MinNCC)		Post-contingency fuel cost ($/h)	
		FixPF	DynPF	FixPF	DynPF	FixPF	DynPF	FixPF	DynPF	FixPF	DynPF
BPF	PSO	2	2	2	2	100.0	100.0	25.3	8.8	878.8	885.6
	GA	5	8	2	3	82.0	93.3	7.3	13.0	899.4	837.5
	SA	5	3	2	2	70.8	91.7	123.6	63.6	923.0	862.8
SPF	PSO	5	3	2	2	85.2	88.9	9.8	8.5	819.5	808.8
	GA	3	2	2	2	69.2	86.7	135.2	36.4	816.9	805.7
	SA	3	3	2	2	75.0	90.6	12.5	11.5	820.9	814.4
LPF	PSO	3	3	2	2	49.1	94.4	23.4	18.4	805.1	797.4
	GA	5	4	2	2	43.2	92.9	229.8	36.2	800.3	798.6
	SA	3	3	2	2	30.8	88.2	256.9	38.7	798.5	799.4
QPF	PSO	4	4	3	2	0.0	88.0	112.2	31.8	879.4	881.1
	GA	4	4	4	2	0.0	87.5	295.5	60.3	800.0	862.8
	SA	4	4	4	2	0.0	83.3	144.2	26.5	817.0	855.6

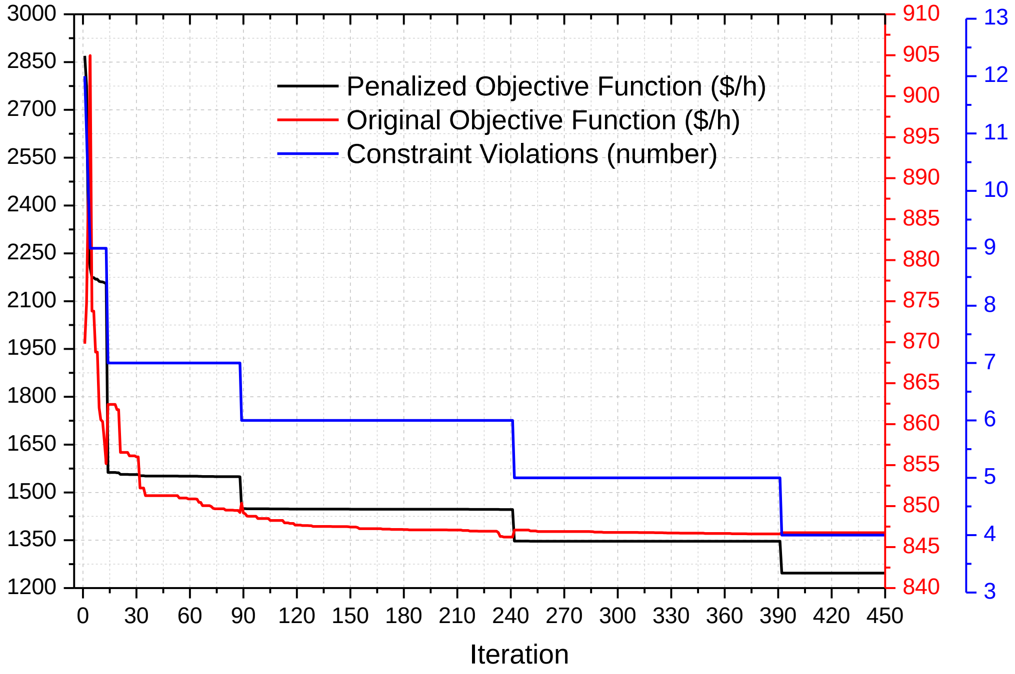


Figure 6.2 Penalized and Original Objective Cost and Constraint Violations (IC3, LPF, DynPF, PSO)

The results in Table 6.3 imply the following observations:

- While the dynamic penalty factor technique helps metaheuristic solvers converging to the MinNCC solution in most of the runs, the number of identified critical constraints can vary in a wide range with fixed penalty factor technique.
- Neglecting some small performance differences between different solvers, the consistency of finding MinNCC for a given solver is improved with dynamic penalty factor technique. This statement is further supported by the less spread between MinNCC and MaxNCC in the case of dynamic penalty factor technique.
- Solver's probability of finding the smallest minimum number of critical constraints (i.e. the minimum of all MinNCCs) is significantly improved when incorporated with the dynamic penalty factor technique. Similarly, the average time required to find MinNCC is in most cases also reduced with dynamic penalty factor technique.
- The combination of QPF with fixed penalty factors is resulting in the extremely poor performance of the solvers, indicated by zero percent success rate. QPF is not working well even with dynamic penalty factor technique, indicated by the relatively large spread between MinNCC and MaxNCC.
- Dynamic penalty factor technique is also improving the quality of the solution, demonstrated by the reduced post-contingency fuel cost when compared to fixed

penalty factor technique. In some cases, fixed penalty factor technique is giving lower fuel cost, but this is achieved at higher MinNCC compared to dynamic penalty factor technique.

- Considering the solution quality, success rate, and the average time to find MinNCC, PSO with LPF is performing relatively better than GA and SA.
- Although BPFs are performing satisfactorily in terms of success rate and the ability to find MinNCC, they suffer in solution quality (i.e. converging to higher objective values). This is obvious because BPFs, being interior penalty functions, always tries to seek feasibility more than the optimality.

6.6. Overview of Constraint Rationalization Framework

As mentioned, there might be violations of many constraints across many locations during the overstressed operating conditions. Operators should address these violations immediately by devising and implementing most effective corrective actions at specific locations and implementing minimum-cost resources, in order to return the system into a normal, or at least alert state. Failure to do so may result in further activation of protection to clear violated constraints and most likely cascaded tripping of network components and network collapse, or network splitting.

Although constraints might be active (i.e. violated) across many locations in the network, typically, only a few of them are critical and mitigation of those critical constraints will resolve all other constraint violations. Knowing the locations of critical constraints, operators can implement techno-economically effective corrective actions utilizing minimal system reserves [99]. In addition, such an approach could avoid unnecessary switching operations and hence prevent further adverse effect on system dynamics in post-corrective state.

6.6.1 Analytical Framework

The proposed operational constraint rationalization framework (CRF) is illustrated in Figure 6.3 and has the following four main stages:

1) Initiate disturbance (i.e. contingency) and perform the analysis of steady-state security constraints in post-disturbance state.
2) Try to mitigate constraint violations through non-emergency corrective controls; if this does not work, proceed to Stage 3

3) Carry out further analysis of security constraints to identify overstressed conditions
4) Select and activate the specific constraint rationalization type

The final stage presents a range of potential options for constraint rationalization depending on the operator priorities. The detailed discussion of each stage is given in the following sections.

6.6.2 Disturbance Initiation and Analysis of Constraints

The evaluation process starts by the occurrence of a disturbance, e.g. a fault resulting in a contingency. For illustration, the disturbances are deliberately chosen as infeasible SCM cases, i.e. these are severe contingencies that result in overstressed operating conditions (Table 6.1).

After protection clears the fault, the system is analysed for constraint violations immediately after the contingency and before the application of any corrective controls. This is carried out by solving an unconstrained power flow with pre-contingency (optimal) control set points applied on a post-contingency configured-network. But, in network operational terms, immediate post-contingency constraint violations are monitored through SCADA system. If any of the security constraint is active or violated, the next step is to mitigate these violations through available non-emergency corrective controls. The total number of immediate post contingency constraint violations (TNSCV) for the considered cases is listed in Table 6.1.

6.6.3 Mitigation of Active Constraints Using Non-Emergency Corrective Controls

This stage tries to compute a feasible and secure operating point (if any) with the activation of only non-emergency corrective controls that are available to the operator (e.g. generation re-dispatch, tap settings, reactive compensation (if any), etc.). This is done by solving relevant SCM problem formulation using either conventional or metaheuristic solver. The selection of the solver type is not important at this stage, as the main point here is to confirm the existence, or non-existence, of a feasible operating point that can be achieved with non-emergency corrective controls. The objective here is to minimize the cost of implementing non-emergency corrective actions (CANECC).

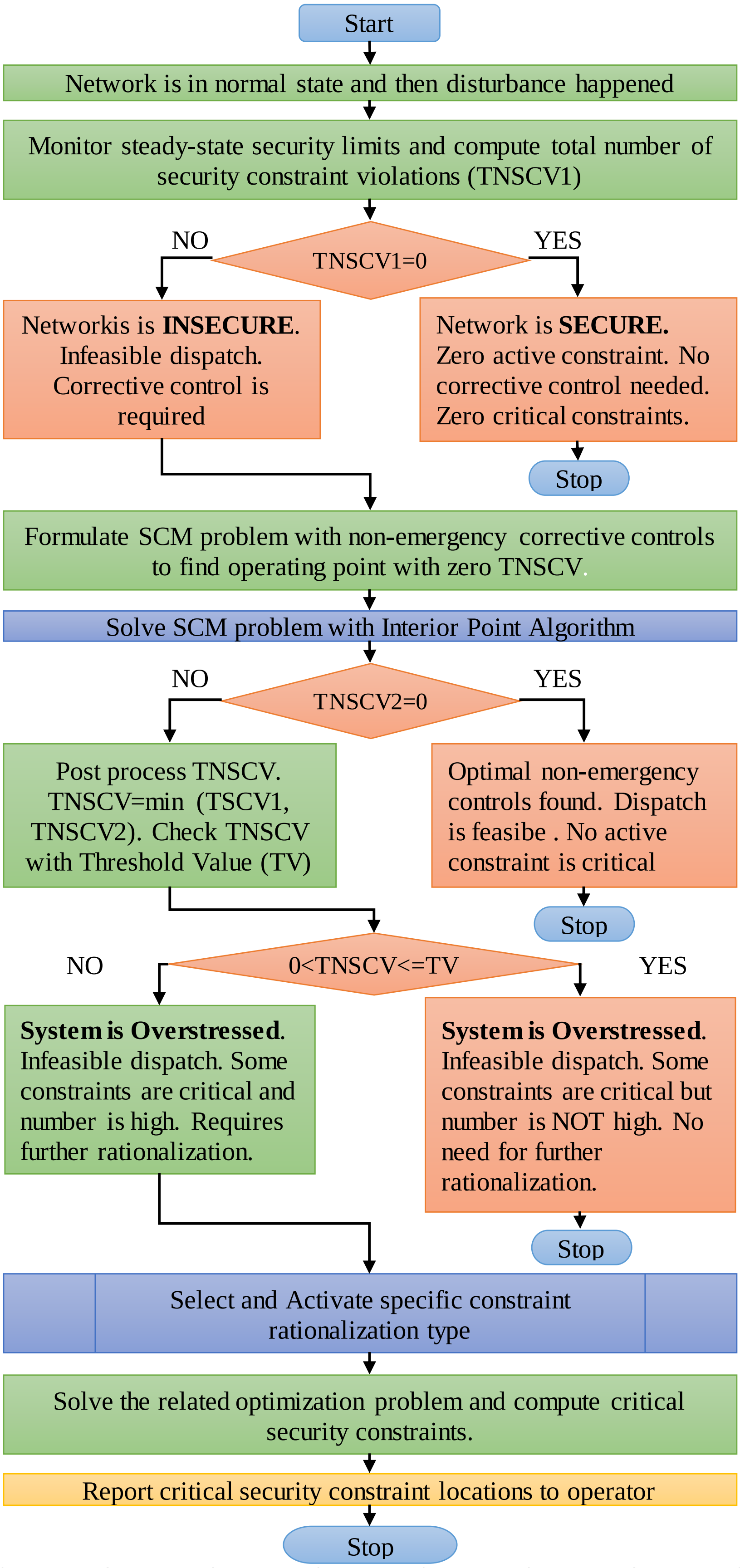


Figure 6.3 Schematic of the Proposed Constraint Rationalization Framework

In terms of the application of the proposed CRF, the conventional solver (PSS/E) is used to confirm the existence (or non-existence) of a feasible operating point. If the solver converges with zero constraint violations, feasible operating point exists and none of the violated constraints is critical. If the solver diverges, or fails to converge, it can be confirmed that a feasible operating point cannot be achieved with only non-emergency corrective controls and system is already in overstressed operating region. This indicates that some of the violated constraints are critical and that they can be mitigated only through emergency corrective controls (also denoted as "remedial actions"). If the solver fails to converge, the number of constraint violations is still the same as TNSCV (but denoted as TNSCV1, in Figure 6.3) because there exists no solution. If the solver diverges with many constraint violations (denoted as TNSCV2) and if these are less than TNSCV, TNSCV is assigned to these constraint violations (i.e. TNSCV = TNSCV2).

The next step is to further process the violated constraints computed in Stage 1 (if the solver fails to converge) or Stage 2 (if the solver diverges with constraint violations) to decide whether to perform constraint rationalization to identify the locations of critical constraints. As the considered test cases are already infeasible, the conventional solver (PSS/E) failed to devise non-emergency corrective control solution, and hence the operator would be interested to find the critical constraints.

6.6.4 Further Analysis of Security Constraints

This section presents a simple logic with which an operator can decide to rationalize the constraints or not. The logic involves the comparison of the total number of security constraint violations (TSCV) against a pre-specified acceptable number of constraint violations. While this pre-specified number can vary based on numerous factors (i.e. network size, operator experience, etc), three is considered as the threshold value in this thesis. If TNSCV is less than a pre-specified threshold, rather than identifying critical security constraints using constraint rationalization, the operator can directly devise remedial actions based on the previous knowledge. However, if the TNSCV is higher than the pre-specified threshold, the operator may not be able to devise a proper remedial action and/or implement it in an effective way without previously rationalizing them. It can be seen from Table 6.1 that the TNSCV for all the considered test cases is higher than the pre-specified threshold value (i.e. three), suggesting that in these cases the operator would benefit from the efficient filtering-out of critical constraints from the total constraint violations.

The next step is to identify the locations of the critical constraints, as this information can help operators in devising and implementing the most effective remedial actions.

6.6.5 Perform Constraint Rationalization

Using the metaheuristic based critical identification process discussed in Section 6.3, this section presents an approach to rationalize or filter the critical constraints from the total violated constraints. The approach rationalizes the constraints based on five operational priorities, where each operational priory is modelled either as an objective function, or as the solver termination criteria (Table 6.4).

If the operator priority is modelled as an objective function, then solver termination criteria are set to a predefined execution time (here, 5 min). If the operator priority is modelled as solver's termination criteria, then the objective function is set to cost of corrective actions (CANECC), because this is assumed to be the default objective for the system operation.

Table 6.4 Classification of Constraint Rationalization

Constraint Rationalization Type	**Operator Priority**	**Objective Function**	**Solver's Termination Criteria**
Identify critical constraints at minimized CANECC	Cost of non-emergency corrective actions	CANECC	Execution time (5 min)
Identify critical constraints within a predefined computational time	Available computational time	CANECC	Execution time (1 min)
Identify a pre-specified size (number) of critical constraints	Pre-specified size of critical constrains	CANECC	Pre-specified size of CC
Identify critical constraints as per available emergency reserves	Available emergency reserves	CANECC	Execution time (5 min)
Identify critical constraints at maximized lead time before the occurrence of the next contingency	Available lead time for next contingency	Lead time	Execution time (5 min)

6.6.5.1 Constraint rationalization based on the cost of non-emergency corrective actions

Here, the operator's objective is to identify the most critical constraints while also minimizing the cost of implementing the non-emergency corrective actions to achieve that minimum constraint solution. The non-emergency corrective controls considered in this thesis are generation re-dispatch, AVR setpoints, transformer tap settings, reactive compensation (if any).

It is assumed that except for the generation re-dispatch, all other non-emergency corrective controls are available with no cost for the operator. Hence, only the cost of re-dispatch is considered as the cost of corrective actions. There are two reasons for this: a) to ease the analysis and b) to represent the practical operational scenarios. To the best of author's experience, system operator, as the owner of the transmission system, can request the re-adjustment of the AVR set points, tap settings and any reactive compensation (this should belong to system operator) for free. Nevertheless, the presented approach can be easily extended to model the cost of any other controls.

Accordingly, CANECC is modelled as the difference between the pre-contingency fuel cost and the post-contingency fuel cost with corrective actions. Two indices *aggregated-percentage-voltage-violation* (APVV), (6.4), and *aggregated-percentage-overloading* (APOL), (6.5), are calculated to quantify the violations of all critical voltage and critical overload/thermal constraints. The sum of APVV and APOL is a measure of the infeasibility (SPINF), (5.2), which was used in Chapter 5 to find MISC.

$$PVVi = \left\{ \begin{array}{c|l} 100 * \dfrac{V_{min} - V_i}{V_{min}} & if\ V_i < V_{min} \\ 100 * \dfrac{V - V_{max}}{V_{max}} & if\ V_i > V_{max} \end{array} \right\} \tag{6.2}$$

$$POLi = \left\{ 100 * \frac{S_i - S_{imax}}{S_{imax}} \middle| if\ S_i > S_{imax} \right\} \tag{6.3}$$

$$APVV = \sum PVVi \tag{6.4}$$

$$APOL = \sum POLi \tag{6.5}$$

where: V_i, S_i – voltage at bus i and apparent power flow in line i, $PVVi$ – percentage voltage violation at bus i, $POLi$ – percentage overloading of line i, APVV, APOL – aggregated voltage violation and overloading for all critical constraints.

All infeasible test cases (IC1-IC10) are analysed to demonstrate this rationalization type. Three metaheuristic solvers with linear penalty functions are employed to solve the selected infeasible cases. The reason to analyse with only linear penalty functions is to limit the attention to the essence of the approach, rather than to the different penalty functions. The list of identified critical constraints, constraint violation amount, and the cost of corrective actions with three solvers are shown in Table 6.5, Table 6.6, and Table 6.7 respectively.

Table 6.5 Critical Constraints Information at Minimized Fuel Cost (PSO)

Test Case	nCC	Indices and Type of CC (CCS)	APVV (%)	APOL (%)	CANECC ($/h)
IC1	2	OL {15, 19}	0.00	60.69	7.04
IC2	1	OL {20}	0.00	36.38	6.11
IC3	4	UV {29, 30}; OL {33, 35}	5.78	48.35	31.39
IC4	4	UV {29, 30}; OL {33, 35}	5.84	64.14	33.55
IC5	2	OL {3,9}	0.00	64.72	15249.86
IC6	1	OL {3}	0.00	50.43	12868.53
IC7	7	UV {24;27;28;29;52;53}; OV {18}	26.70	0.00	3311.12
IC8	6	UV {24, 27, 28, 29, 52, 53}	32.83	0.00	775.86
IC9	2	OL {135, 137}	0.00	25.24	46.27
IC10	3	UV {24, 84, 85}	20.54	0.00	28.21

OL{i}: Overloading of line i; UV{i}, OV{i}: Undervoltage and Overvoltage at bus i

Table 6.6 Critical Constraints Information at Minimized Fuel Cost (GA)

Test Case	nCC	Indices and Type of CC (CCS)	APVV (%)	APOL (%)	CANECC ($/h)
IC1	2	OL {15, 19}	0.00	60.88	8.17
IC2	1	OL {20}	0.00	36.61	7.79
IC3	4	UV {29, 30}; OL {33, 35}	5.59	47.16	46.89
IC4	4	UV {29, 30}; OL {33, 35}	5.84	64.14	76.36
IC5	2	OL {3,9}	0.00	68.60	15990.96
IC6	1	OL {3}	0.00	43.92	15674.27
IC7	6	UV {24;27;28;29;52;53}	35.79	0.00	3355.71
IC8	6	UV {24, 27, 28, 29, 52, 53}	30.21	0.00	724.79
IC9	2	OL {135, 137}	0.00	31.30	46.06
IC10	3	UV {24, 84, 85}	16.92	0.00	34.07

CC – Critical constraint; nCC – Number of CC; CCS – Critical constraint set

Table 6.7 Critical Constraints Information at Minimized Fuel Cost (SA)

Test Case	nCC	Indices and Type of CC (CCS)	APVV (%)	APOL (%)	CANECC ($/h)
IC1	2	OL {15, 19}	0.00	60.88	9.02
IC2	1	OL {20}	0.00	37.22	8.82
IC3	4	UV {29, 30}; OL {33, 35}	5.61	36.48	77.25
IC4	4	UV {29, 30}; OL {33, 35}	5.84	64.13	59.21
IC5	2	OL {3,9}	0.00	64.72	15249.86
IC6	1	OL {3}	0.00	44.02	14978.25
IC7	7	UV {24;27;28;29;52;53}; OV {18}	28.52	0.00	3513.99
IC8	9	UV {24, 26, 27, 28, 29, 31, 52, 53}; OV {18}	75.24	0.00	1107.40
IC9	2	OL {135, 137}	0.00	29.39	45.99
IC10	3	UV {24, 84, 85}	18.09	0.00	12809.98

CC – Critical constraint; nCC – Number of CC; CCS – Critical constraint set

Following observations can be made from the above results:

- Neglecting the small differences in bus voltage limit violations (APVV) and branch overloads (APOL), all solvers, except for two cases (IC7 and IC8), are reporting the same set of critical constraints.
- For the test cases IC7 and IC8, the performance of PSO and SA are inferior to GA, as they are unable to identify the minimum set of critical constraints.
- While the indices of critical constraints identified here and the indices of MISC identified in Chapter 5 are same, the amount of constraint violations associated with CCS (i.e. APVV+APOL) is either equal to or larger than the violations associated with MISC (Table 5.10). This is where CCS differs from MISC. While the constraints in MISC are identified to minimize the infeasibility from purely mathematical sense, constraints in CCS are identified to minimize the operator's current objective. Hence, CCS and MISC can generally share the same constraints, but they could be different as well.
- While the MISC is unique for a given infeasible problem, the size and violation of CCS can be varied by modelling the various operator's priorities. Nevertheless, the size of the CCS will be always equal to or higher than the MISC. This is evidenced with test case IC7, where the size of the CCS reported by PSO and SA is a superset of the corresponding MISC.
- The higher cost of corrective actions (CANECC) for IC5 and IC6 indicates that these SCM cases are severe and require re-dispatch of expensive generators from

their pre-contingency generation set points.

- Although the cost of corrective actions is seemingly small for other test cases (IC1-IC5, IC8-IC10), one should remember that the operator might pay much higher price for emergency corrective controls, in order to resolve the remaining constraint violations (nCC).

To sum up, the proposed framework not only reduces the cost of non-emergency corrective actions to resolve most of the constraint violations (except CCS), but also helps the operator to identify where to activate the emergency reserves and what these reserves should be. For example, the CCS for IC10 can be resolved by activating emergency reactive compensation at Buses 24, 84 and 85, or at the buses that have higher reactive power injection sensitivity to voltages at these buses.

6.6.5.2 Constraint Rationalization Based on Available time

If the operator knows the service restoration time of the components (lost due to a contingency), as well as the time before tripping/losing the next component (e.g. overloading of a line due to a contingency), the operator would like to find a list of critical constraints based on the available lead time. Hence, the operator priority (available lead time) is modelled as solver's termination criteria while the objective function is set to CANECC. It should be noted that the lead-time is specific to network types and configurations, types of contingencies and post-contingency constraint violations and other numerous factors.

Nevertheless, for demonstration purposes, this section analyses all ten test cases from Table 6.1 with a lead time of one minute. Again, three metaheuristic solvers with linear penalty functions are employed to solve the considered test cases. The minimum and the maximum number of critical constraints identified within one-minute execution time, as a percentage of immediate post-contingency constraint violations (TNSCV) over 50 runs are presented in Table 6.8.

Table 6.8 Constraint Reduction within a One Minute (as a percentage of TNSCV)

Test Case	PSO		GA		SA	
	Max Reduction	Min Reduction	Max Reduction	Min Reduction	Max Reduction	Min Reduction
IC1	50.00	50.00	50.00	50.00	50.00	50.00
IC2	90.91	90.91	90.91	90.91	90.91	90.91
IC3	55.56	22.22	55.56	22.22	55.56	22.22
IC4	50.00	25.00	50.00	12.50	50.00	12.50
IC5	77.78	33.33	77.78	0.00	77.78	0.00
IC6	85.71	57.14	85.71	57.14	85.71	42.86
IC7	85.00	0.00	85.00	0.00	80.00	0.00
IC8	60.00	0.00	65.00	0.00	55.00	0.00
IC9	80.00	80.00	80.00	80.00	80.00	70.00
IC10	72.73	63.64	72.73	54.55	72.73	36.36

The results imply the following observations:

- Significant reduction in constraint violations: all solvers, for most of the test cases, can find a solution with a reduced percentage of constraint violations when compared to immediate post-contingency constraint violations. This confirms that this kind of constraint rationalization can be very useful for network operators when faced with similar situations.
- For some test cases, solvers may fail to find any solution with reduced constraint violations. For example, there are few situations (e.g. IC7 and IC8) for which the minimum percentage of constraint reduction is zero, which means solvers are unable to reduce the number of immediate post-contingency constraint violations within one minute. There might be two reasons for this: the considered test cases are too severe, and/or the execution time of one minute is not enough to find a minimum constraint solution.

6.6.5.3 Constraint Rationalization to minimize number of violations to a pre-specified number

The objective, in this case, is still minimization of CANECC, but the operator runs the optimization solver until some pre-defined number of constraint violations are achieved. For example, the operator wants to run the program until he sees an X% reduction in the total constraint violations (TNSCV). The target value of the percentage reduction is entirely up to the operator's decision. The operator may take a decision based on his previous experience with similar situations, network knowledge, and the present status of the network.

Nevertheless, for demonstration purposes, this section analyses all test cases from Table 6.1) with 50% constraint reduction as a threshold value. Again, three metaheuristic solvers with linear penalty functions are employed to solve selected test cases. The times (averaged over 50 runs) required to reduce constraint violations by 50% (or less) for three solvers are listed in Table 6.9. Furthermore, the process of constraints reduction over the PSO solver's execution time for two test cases IC9 and IC10 are plotted in Figure 6.4.

The results indicate that the solvers can reduce number of constraint violations to 50% (or less) in a reasonable time, except for the test cases IC7 and IC8. It was observed during the analysis that test cases IC7 and IC8, irrespective of the used metaheuristic solver, always require higher computational time. This is because the post-contingency network experiences many constraint violations at different locations and the solvers must perform an extensive search in order to find solutions that can resolve most of the constraint violations. Nevertheless, PSO is performing superior to GA and SA.

Table 6.9 Average Computation Time (s) to Reduce Constraint Violations by 50% (or lesser)

Test Case	PSO	GA	SA
IC1	5.42	20.37	15.86
IC2	1.13	6.83	9.22
IC3	10.70	18.41	24.35
IC4	17.60	27.53	18.62
IC5	11.54	24.85	22.13
IC6	6.60	14.27	8.85
IC7	99.18	152.27	128.51
IC8	113.52	202.07	171.08
IC9	30.02	27.30	41.82
IC10	51.29	51.36	51.59
Aggregated Average	34.70	54.53	49.20

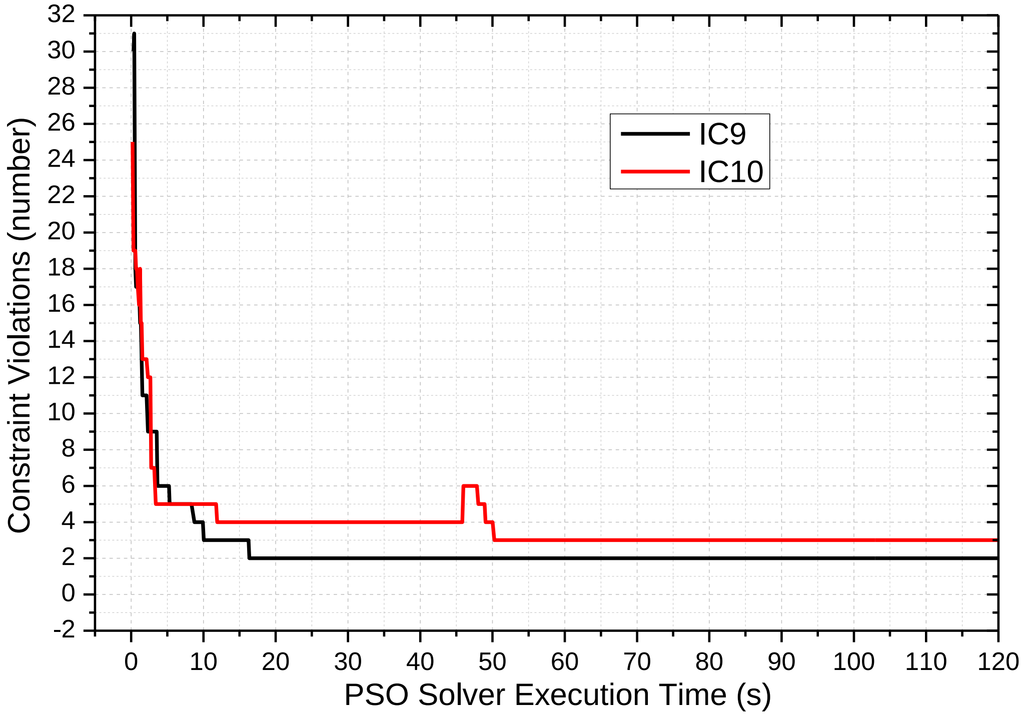


Figure 6.4 Number of constraint Reduction Versus PSO Solver Execution Time

6.6.5.4 Constraint Rationalization Based on Available Emergency Reserves

This constraint rationalization focusses on the possibility of shifting critical constraint types from one to another (e.g. critical voltage constraints to critical thermal constraints). The dynamic penalty factor updating technique allows the operator to shift the constraint types in the final critical constraint set by varying the initial penalty factor values applied to bus voltage and line thermal limits violations. While voltage violations are mitigated by reactive power reserves, thermal violations are mitigated through active power reserves.

If the network possesses more active reserves than reactive reserves, the operators may want to find a critical constraint set in which there are more thermal limit violations, than voltage bus limit violations. Similarly, the operator may want to find a critical constraint set which has more voltage violations if the network has more reactive power reserves. Moreover, some reserves may be available only at specific locations in the network, or reserves of the same type available at many locations but a single bus cannot take care of all constraint violations.

This is achieved by varying the values of the initial penalty factors for voltage and thermal violations, where fewer voltage violations and more thermal violations will be achieved by inputting larges penalty factors for voltage violations and smaller penalty factors for thermal violations, and vice versa.

It should be noted that the shifting of constraint types is not always possible or might be very difficult. Very few practical situations allow the operator to perform this kind of constraint rationalization. This section analyses two such test cases (IC8 and IC10) for which constraint shifting is possible. The analysis here is focussed on the possibility of shifting an undervoltage constraint at one bus to multiple overvoltage constraints at different buses. This is achieved by assigning lower penalty (i.e. 10) to overvoltage constraints compared to undervoltage constraints (i.e. 100). For example, the undervoltage constraint at bus 53 (for IC8 in IEEE 57-bus network) is shifted to overvoltage constraints at bus 45 and bus 55 (Table 6.10). A similar explanation applies to IC10.

Table 6.10 Constraint Rationalization Based on Reserves

	Original Constraint Violations	Shifted Constraint Violations
IC8	UV{24, 27, 28, 29, 52, 53}	UV{24, 27, 28, 29, 52}, OV{45, 55}
IC10	UV{24, 84, 85}	UV{24, 84}, OV{95, 137}

6.6.5.5 Constraint Rationalization to Maximize the Leadtime for Next Contingency

Here the operator is not interested to minimize the number of violations but aims to maximize the lead time available before the next contingency, e.g. losing the next overloaded line due to activation of overloading protection. This aspect of the analysis is very important and useful from the context of modern electricity networks, which frequently operate near security limits in order to maximize the revenues, or due to contractual obligations. As time is precious, reserving a few minutes of lead-time can even avoid a blackout, especially during the overstressed operating conditions. Increased lead time will also allow for utilising generators with longer ramp-up times and will generally provide more room for the existing controls to respond and devise more effective remedial actions.

The concept of lead time is derived from the dynamic thermal rating of transmission lines [11]-[12]. Following a severe contingency, many lines may be overloaded, but their temperature may not reach their maximum temperature instantaneously. They require some time to reach the maximum temperature and this time is considered as the available time before line tripping takes place. Every overloaded line may have a different available time before tripping, and the minimum of the all available times for all the overloaded lines is considered as the lead time in this section. A function to calculate this lead time is developed (6.6) and is maximized during the optimization process. The detailed mathematical formulation of the thermal modelling of overhead transmission lines and the derivation of lead time is explained in Appendix B.

$$Leadtime_k = -\tau \ln[\frac{T_{cf} - T_{cmaxt}}{T_{cf} - T_{ci}}] \tag{6.6}$$

where: $Leadtime$ – lead time for line k, T_{cf}, T_{ci} – conductor surface temperatures during steady state, τ – time constant, T_{cmaxt} – maximum temperature limit in post-contingency state.

The optimization problem is formulated to maximize the lead-time, (6.7) – (6.8). Two test cases (IC1 and IC2) are analysed to demonstrate this approach using only one solver (PSO). Table 6.11 presents the results: the maximized lead time, indices and violation amount for the violated constraints at maximized lead time. The lead time against the solver's execution is plotted for two test cases (IC1 and IC2) in Figure 6.5. The solver terminates execution at 40 s, as there is no change in lead time from 15s. The results indicate that the maximum overloaded line (T7-9) for test case IC1 achieves its peak temperature after around 440 seconds (i.e. slightly above 7 min), when the protection will trip that component afterwards. This is the time available for the operator to take an action to mitigate the post-contingency critical constraint violations. A similar explanation applies to other test cases.

$$\text{Maximize: } min\ (Leadtime) \tag{6.7}$$

$$s.to\ \ g = 0\ and\ h \leq 0 \tag{6.8}$$

Table 6.11 Critical Constraint Information at Maximized lead-time for next tripping

Test case	Lead time (s)	Indices of violated constraints (overloaded lines)	Amount of violation (extra load in percentage)
IC1	439.24	OL {T7-9, L10-11, L12-13}	OL {21.02%， 10.89%, 8.90%}
IC2	428.03	OL{L13-14}	OL {27.25%}

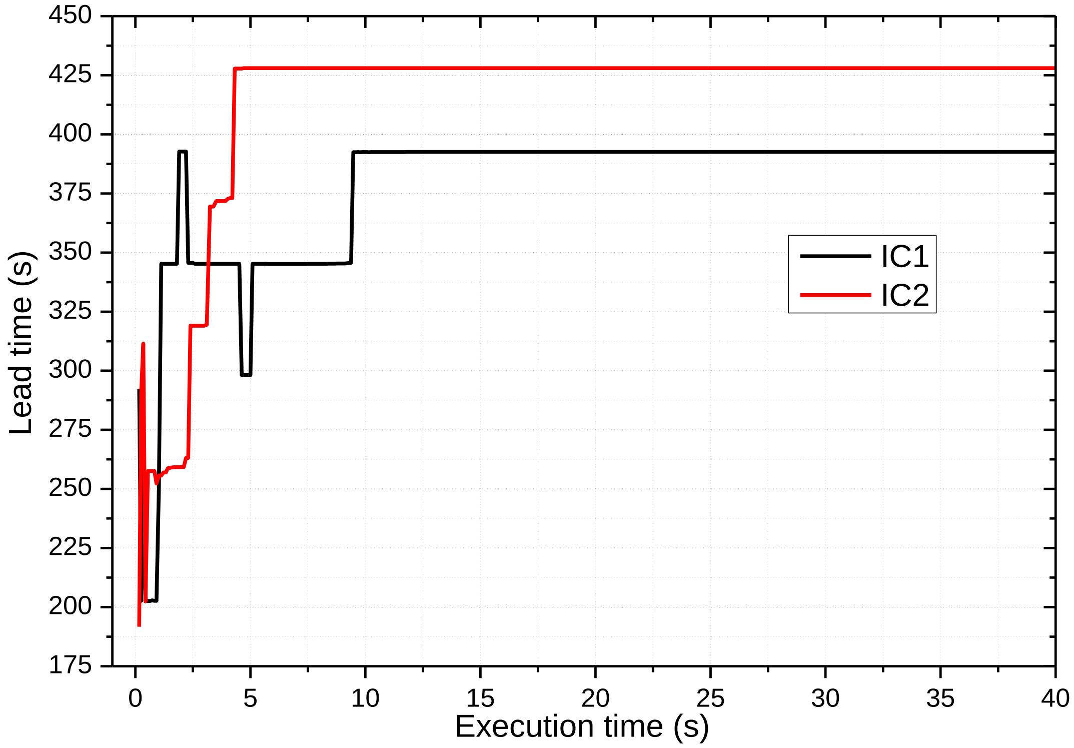


Figure 6.5 Leadtime Versus Solver Execution Time (IC1 and IC2)

6.7. Conclusions

This chapter presented a novel constraint rationalization framework to identify the types and locations of critical security constraints during the overstressed system operating conditions. The framework acknowledges that the criticality of a constraint violation will vary based on the operator's evaluation and prioritisation of post-contingency controls and actions. The framework enables the operator to identify the critical constraints sets (CCS) according to specified priorities. The framework was illustrated by modelling five different types of operator priorities (cost of corrective actions, available computational time, pre-specified number of CCS, available resources, and available lead time before the next contingency occurs) and it can be easily extended to include other priorities which an independent system operator (ISO) may want to consider during the overstressed conditions (e.g. minimization of corrective actions in post-contingency state). This clearly suggest further potential of exploring this aspect of constraint management (and presented framework).

The framework is demonstrated with several overstressed test cases on considered test networks. The presented results indicate the benefits of the framework to the operators. The identification of types as well as locations of the critical constraints is very important during overstressed conditions. While the type of critical constraints helps operators in deciding what type of remedial actions should be selected or activated, the locations of critical constraints help operators to identify where and how to implement these remedial actions optimally, so that the network safely transits to a new secure operating state, without violation of any dynamic security constraints during the transition (This is demonstrated in Chapter 7).

This framework could improve the decision-making capability at energy control centre. For example, an operator typically cannot process more than five alarms at a time and the presented constraint rationalization framework could pinpoint the critical alarms, so that the operator can devise most efficient decisions quickly. In the worst case, if the load shedding inevitable, at least the lowest amount of load to be disconnected can be computed, as well as where this load is to be disconnected. In order to illustrate these important applications of the proposed framework, Chapter 7 presents a remedial action framework, in which information on the types and locations of critical constraints from this chapter is used to devise the most effective remedial actions and to implement them in optimal way.

Chapter 7

Remedial Action Selection and Implementation Framework

This chapter presents a framework to select and implement the most effective (response-driven) remedial actions to mitigate critical constraint violations during overstressed operating conditions.

7.1. Introduction

The management of static security constraints (bus voltages and branch thermal limits) is one of the continuous and critical tasks performed by operators. In order to accommodate higher shares of renewable generation resources and defer infrastructural investments, modern electricity networks are extensively operated close to their technical security limits. Hence, constraint management remains to play a major role in ensuring secure and efficient network operation. Static security constraints at any operating point can be divided into *noncritical constraints* (NCC) and *critical constraints* (CC). To be statically secure, the system must always fulfil both types of security constraints.

Depending on the generation (especially renewable generation) and demand patterns, and outages, violations of security constraints will appear and disappear in real-time [28]. In principle, there exist two types of corrective controls (non-emergency and emergency corrective controls) to mitigate constraint violations. In smart grid context, both types of controls can be automatic, or operator initiated. However, in the first instance, operators use non-emergency corrective controls (NECC) to resolve constraints. If NECC does not resolve all constraint violations, emergency corrective controls (ECC) will be activated.

Following a disturbance, the readjustment of NECC may or may not resolve all the resulting constraint violations. If NECC resolves all constraint violations, the corresponding disturbance cannot develop overstressed or emergency conditions. The constraint violations that can be resolved by NECC controls are denoted as NCC and the ones that cannot be resolved are denoted as CC. The violation of at least one critical constraint indicates that the system is overstressed, which typically happens following a severe contingency [14].

Noncritical constraint violations (NCCVs) can be managed with NECC. On the other hand, critical constraint violations (CCVs) require prompt activation of ECCs, referred to as remedial actions to prevent further activation of protection, triggering cascaded tripping possibly leading to a blackout [3]. The set of NCCVs and CCVs are denoted as noncritical constraint set (NCCS) and critical constraint set (CCS), respectively. If the transition from pre-contingency to the post-contingency state involves only NCCVs, an experienced operator may successfully select the adequate non-emergency corrective actions to manage all violated constraints. However, if the transition involves CCVs, the most effective remedial actions must be computed algorithmically, as it will be difficult for an operator to select appropriate remedial actions based on previous experience [100].

In this context, control centres are integrating advanced OPF modules to their EMS (energy management system) to effectively control emergency reserves and devise optimal remedial actions for managing constraint violations [101]. In the case of an overstressed system, featuring one or more CCVs (which are not known *a priori*), conventional OPF solvers will fail to converge and compute the required control action, as the corresponding optimization problem becomes mathematically infeasible. This has already been demonstrated in Chapter-4, Chapter 5 and Chapter-6.

For a given overstressed system, the identification of CCS is essential from both the optimization and the operational points of views. As per the optimization, CCVs are the actual cause of infeasibility. From an operational point of view, CCVs indicate where in the network and in relation to which network components optimal remedial actions should be planned and activated. Unlike in linear OPF programs, no commonly accepted method exists in nonlinear OPF programs for identification of CCVs [3]-[4]. Moreover, the type, location, and amount of violation of CCS can be varied based on operator or control priorities. While Chapter-5 presented an infeasibility diagnosis framework (IDRF) to identify CCS purely from optimization viewpoint, Chapter-6 presented a constraint rationalization framework (CRF) to identify CCS from the operations viewpoint. This chapter, using CRF, presents a novel remedial action selection and implementation framework (RASIF) to diagnose overstressed conditions as well as devise the most effective remedial actions.

Literature Review: Remedial action schemes (RAS) are extensively used to enhance system stability and mitigate thermal overloading and bus voltage violations after contingencies [102]. RAS, if implemented properly, can increase the flexibility in power system operation [103]. A detailed review of industry experiences with RAS is available in [104]. From the author's view, the only difference between the ECCs and RAS is that RAS represents the action of implementing an ECC in a specific way and in specific situations. RAS is also denoted as special protection schemes (SPS).

In general, RAS can be divided into event-driven RAS and response-driven RAS [51]. Event-driven remedial actions are fit and forget type controls and are executed automatically after the occurrence of a specific event. Contrastingly, response-driven remedial actions are computed by the EMS after system enters the emergency operating region. Unlike event-driven remedial actions, response-driven remedial actions can be re-adjusted and re-applied until there is an improvement in system performance. The remedial actions discussed in this thesis are response-driven remedial actions.

Traditionally, RASs are designed based on planning analysis and they are event-driven and fixed (e.g. RAS attached to a specific or set of contingencies [102]). As the system evolves over time, the same contingency can have different severity in different operating conditions (e.g. an unexpected generation or demand profile can change the definition of a contingency). Consequently, the planning based, and even-driven remedial actions can be ineffective from the technical or economic viewpoint. Moreover, most of the previous RAS are motivated by only technical rather than economic reasons [103]. This assumption no more works in the re-regulated environment.

Recently, an active research work is going on in academia and industry to devise response-driven RAS in the operations environment, using system physical models and/or real-time measurements. For example, RAS to mitigate small signal and transient stability, frequency and voltage stability, and voltage collapse are proposed in [105]-[109]. Moreover, several ISOs are also interested in devising new RAS to effectively manage their emergency reserves [110]-[111]. There has been much previous work on CM and VVC based on the use of generation rescheduling and load shedding [112]- [115], distributed generation [116]-[117], FACTS devices [118]-[120], demand-side-management [121]-[122], energy storage [123], and transmission switching [124]-[126].

Earlier studies were mostly concerned with contingencies that will push the system into an alert state and paid less attention to overstressed operating conditions, where, if adequate control actions are not promptly implemented, changes in power flows and power balance will result in the inability of conventional solvers to converge and compute the required remedial action. In addition, especially from the context of constraint management, the steady state and dynamic security analysis in most of the earlier works is addressed separately. Neglecting the violation of steady state security constraints and the corresponding protection operations, a system may successfully transit from pre- to post-disturbance state. In this case, the state trajectory or system is dynamically secure, but the post-disturbance state may or may not qualify for the steady state security. If it is not, protection system will trip the overloaded lines which introduce further dynamics and the network may not reach the steady state.

Moreover, there exists no work on computing remedial actions based on the type, location and amount of violation of critical constraints to resolve overstressed operating conditions. In conclusion, to the best of author's knowledge, the presented framework (RASIF) is the very first methodological attempt to address the issue of selecting and implementing the most effective remedial actions for the overstressed systems, with the identification of critical constraints as root causes for the overstressed operating conditions.

The rest of the chapter is organized as follows: Section 7.2 outlines the proposed remedial action framework and describes the implementation of various remedial actions. Simulation results on the test networks are presented in Section 7.3. The main contributions, observations, and limitations of the approach are discussed in Section 7.4. Section 7.5 concludes the chapter.

7.2. Overview of Proposed Remedial Action Framework

7.2.1. Analytical Framework

As mentioned, (prolonged) operation of the network with CCVs will result in further activation of the protection system, leading to a cascaded tripping and (extreme) emergency operating conditions. Only emergency corrective controls referred to as remedial actions can mitigate these constraint violations and return the system to a normal or (at least) alert operating region.

Typically, under overstressed operating conditions, networks experience the violation of numerous constraints (i.e. branch overloading and bus under/over voltage alarms) and some of these violations are critical. These CCVs must be addressed immediately, or else the network loses its integrity and bifurcated into islands. The operator, being in charge, should devise the techno-economically effective remedial actions and implement them at the best locations to relieve CCVs. As the network is already overstressed, failure to do so might further degrade system security.

The implementation of devised remedial action should need a minimal number of switching and control operations to minimize the usage of system reserves and prevent the further adverse effect on system dynamics in the post-corrective state [127]. In this context, a novel remedial action selection and implementation framework (RASIF), using previously developed constraint rationalization framework (CRF, Chapter-6), is proposed here to diagnose overstressed operating conditions, as well as derive and implement the most effective remedial actions.

The framework is illustrated in Figure 7.1 and has the following four main stages:

1) *Analysis of post-disturbance operating conditions* – this stage involves disturbance simulation and identification of number (TNSCV), type and location of violated constraints.

2) *Computation of non-emergency corrective control (NECC) solution* – if stage-1 reports nonzero TNSCV, this stage employs a conventional SCM solver to compute an NECC solution with an aim to resolve all constraint violations. If the SCM solver cannot find a solution, stage-2 employs IDRF (see chapter 5) to confirm the non-existence of the NECC solution.

3) *Identification of CCVs* – if stage-2 confirms no NECC solution, this stage, for a given operator priority, identifies the CCVs by using CRF framework (see chapter 6).

4) *Classify the SCM problem and employ relevant remedial action(s)* – this stage, based on the nature of CCVs, classifies the SCM problem into either CM or VVC; and implement relevant remedial action(s).

The final stage considers a range of potential solutions for a remedial action depending on whether the CCVs involve thermal or voltage constraints. Accordingly, this thesis considers: distributed generation (DG) dispatch, demand-side-management (DSM), reactive power control, and load shedding. The stages of the framework are explained in the following sections.

7.2.2. Analysis of Post-disturbance Operating Conditions

The evaluation process starts by the occurrence of a disturbance, e.g. a fault resulting in a contingency. For illustration, the disturbances are deliberately chosen as infeasible SCM cases, i.e. these are severe contingencies that result in overstressed operating conditions. After the protection clears the fault, the system is analysed for constraint violations immediately after the contingency, before the effect of any corrective control. This is carried out by solving an unconstrained power flow with pre-contingency (optimal) control set points applied on a post-contingency configured-network. But, in the operations environment, immediate post-contingency constraint violations are monitored through the SCADA system.

The total number of security constraints violations are denoted as TNSCV. If any of the security constraints are violated (i.e. nonzero TNSCV), the next step is to resolve these violations by re-adjusting (non-emergency) corrective controls using an SCM solver.

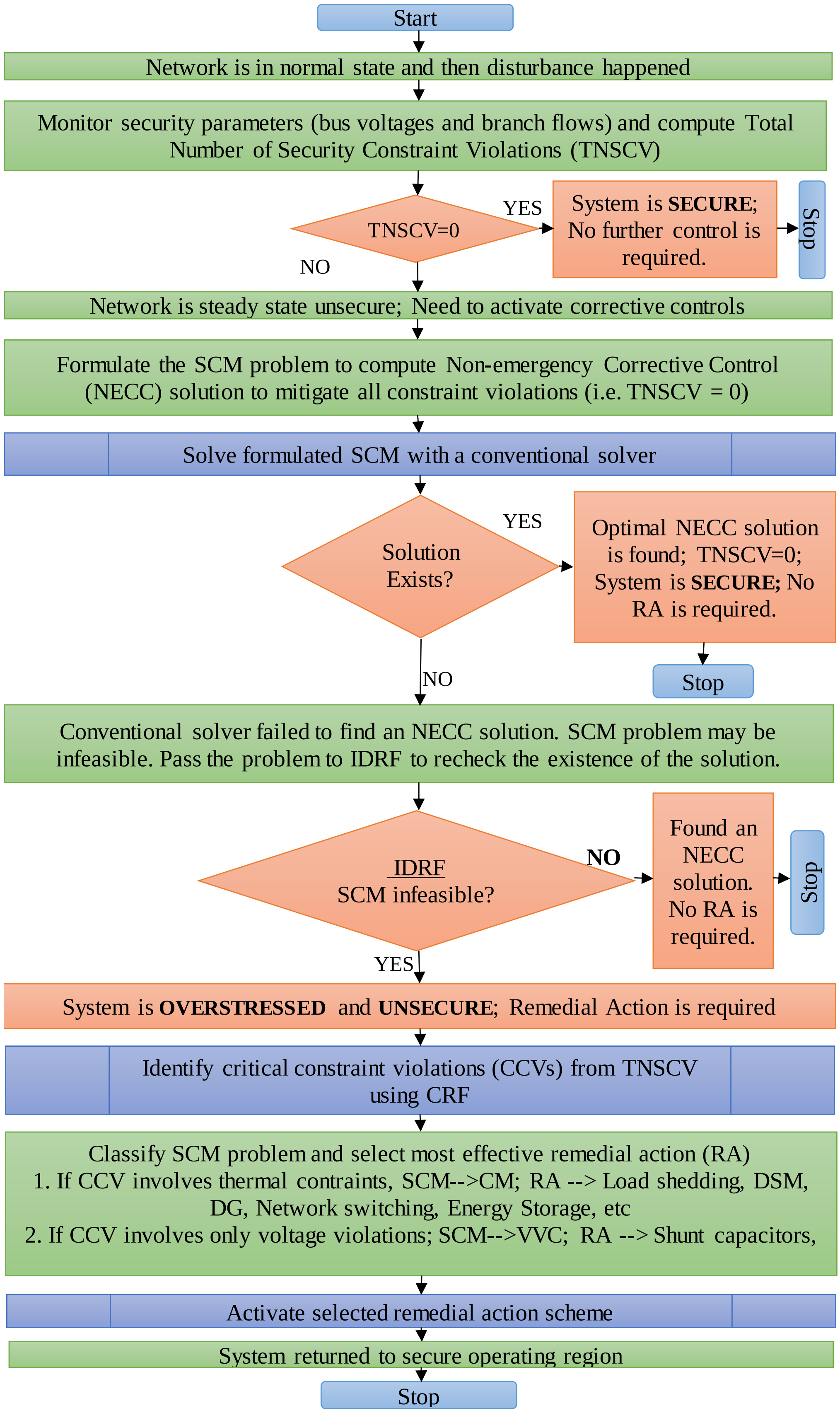


Figure 7.1 A General Methodology for Devising Optimal Remedial Actions

7.2.3. Computation of Non-Emergency Corrective Control Solution

The purpose here is to find a feasible and secure operating point with zero constraint violations by solving related SCM problem. This employs a conventional SCM solver to find the optimal settings for available non-emergency corrective controls, NECC (generator outputs, PV bus voltages, transformer tap settings, reactive compensation, etc.). The SCM problem is formulated to minimize the cost of implementing available non-emergency corrective controls (CANECC) while satisfying specified equality and inequality constraints, (7.1)–(7.2). Please refer to chapter-6 for details about modelling CANECC.

$$min. \quad CANECC \tag{7.1}$$

$$s.t. \quad g = 0 \; and \; h \leq 0 \tag{7.2}$$

An interior point optimization method (PSSE) from [155] is employed as the conventional SCM solver. If the solver converges, the settings of NECC's define a secure system, which can be implemented with no further remedial action required. However, if solver fails to converge and compute an NECC solution, the SCM problem under test will be forwarded to IDRF in order to confirm the existence and non-existence of the NECC solution. If IDRF confirms no solution, the system is overstressed, and additional steps are required –the formulated SCM problem, (7.1)–(7.2), will be forwarded to CRF to identify the CCVs.

7.2.4. Identification of CCVs using CRF

While an overstressed system can experience both critical and noncritical constraint violations, corrective actions on critical constraints can manage both. From an optimization viewpoint, critical constraints are the minimal set of constraints causing the search space to be empty or infeasible. Hence the identification of CCVs is essential for devising proper corrective actions to mitigate the overstressed situations.

This section employs the CRF (see Chapter 6) to rationalize the total violated security constraints (i.e. TNSCV) and identify the CCVs. For the demonstration purposes, here constraint rationalization is performed to minimize CANECC. But the operator could impose any other priority as and when required.

7.2.5. Defining Most Effective Remedial Actions

The final stage is to use the knowledge of the CCVs to define the most effective remedial actions for returning the system to secure state. After CCVs are identified, this can be done with either conventional or metaheuristic algorithm based SCM. For that purpose, two factors are calculated [202]: a) active power injection sensitivity factor for branch flows (PISF), which captures the sensitivity of the flow through a branch between bus i and j with respect to a change in active power injection at bus k, and b) reactive power injection sensitivity factor for bus voltages (QISF), which captures the sensitivity of the voltage at bus i with respect to reactive power injection at bus k (slack bus constraint included).

$$PISF_{ij}^{k} = \frac{\partial S_{ij}}{\partial P_k} = \frac{\Delta S_{ij}^{k}}{\Delta P_k}\ ; k \in B\ and\ (ij) \in L \tag{7.3}$$

$$QISF_{i}^{k} = \frac{\partial V_{i}}{\partial Q_k} = \frac{\Delta V_{i}^{k}}{\Delta Q_k}\ ; i \in B\ and\ k \in B \tag{7.4}$$

where: B is bus index; L is line/branch index; ΔP_k and ΔQ_k are the changes in active and reactive power injection at bus k; ΔS_{ij}^{k} is a change in apparent power flow in a branch (i, j) due to ΔP_k; ΔV_i^k is a change in voltage at bus i due to ΔQ_k.

If CCVs involve only voltage limit violations, the corresponding SCM is a VVC (volt/var control) problem and the effective remedial action should be the one which can control reactive power injection at some critical buses. If CCV involves a mixture of voltage and thermal limit violations or only thermal limit violations, the corresponding SCM is a CM problem and the effective remedial actions should be the one which can control both active and reactive power injection. While the precise implementation depends on the intervention considered (DG control, DSM, load shedding, etc.) and is best described in the case study, the general process is to:

1. Calculate PISFs (or QISF) for all buses with respect to the critically overloaded branches (or critical undervoltage buses)
2. Select the buses with the highest absolute PISF (or QISF) values as target buses for implementing selected remedial action and incorporate corresponding parameters (e.g. load or generation at these buses) as new control variables in the SCM formulation;

3. Solve the modified SCM employing relevant objective functions corresponding to the intervention considered.

7.2.5.1 Remedial Action – Optimal Control of Distributed Generation

In the context of smart grid functionalities, optimal dispatch of DG can be viewed as a credible approach to support network security and operational reliability. In this thesis, optimal dispatch of DG active power is considered to relieve branch thermal as well as bus voltage congestions during overstressed operating conditions. The target buses are those with the highest PISF (absolute) values. The modified SCM problem considers DG active power production as a control variable and has two objective functions: minimize overall fuel cost ("OFC", including DG fuel cost) and active power losses ("L") to optimally dispatch DG in addition to regular generation to resolve CCVs. One should note that, in the case of renewable-based DG, the term schedule means only output reduction.

7.2.5.2 Remedial Action – Optimal Reactive Power Injection

When a system experiences many under/over voltages due to reactive power imbalance, an effective approach may be to install and control reactive power reserves at certain critical buses. In this thesis, optimal placement, and control of shunt capacitors for improved volt-var control (VVC) is employed at buses where critical undervoltages occur. The target buses have the highest QISFs with respect to the voltages at critical buses. Shunt capacitors of 20 MVAr (each) are placed on the target buses and the values of shunt capacitors are considered as a (continuous) control variable in the SCM formulation. Again, the modified SCM problem is solved separately for three objective functions: minimize fuel cost ("F"), losses ("L"), and shunt capacitor use ("S").

7.2.5.3 Remedial Action – Coordinated control of generation and demand

The "last resort" emergency remedial action available to network operators to resolve CCVs is load shedding. Three demand control approaches: (i) hard load shedding (HLS), (ii) optimal load shedding (OLS), and (iii) selective optimal load shedding (SOLS) are proposed in this thesis. These approaches differ in terms of selected target buses and the proportion of demand available to control.

Hard Load Shedding (HLS): HLS approach is initiated by the protection system (mostly) and sometimes by the operator. The target buses for the HLS approach are typically associated with immediate post-contingency violations (i.e. overloaded branches, under/overvoltage buses following a contingency). In general, HLS approach completely shed the load at the target buses (100% load shedding).

Optimal Load Shedding (OLS): OLS approach computes the optimal amount of load to shed using an optimization program. The target buses for OLS are the buses where immediate post-contingency constraint violations occur. OLS consider the loads at target buses as control variables and compute the optimal load to shed by using an SCM solver. Hence, shed value of the load at the target buses can be anywhere between 0% and 100%.

Selective Optimal Load Shedding (SOLS): Compared to HLS and OLS, SOLS approach chooses only a smaller number of buses as target buses for the shedding. It selects target buses based on their sensitivity to influence power flows in overloaded branches, or voltages at under/over voltage buses. In other words, these are the buses that have the highest active/reactive injection sensitivity factors (PISF and QISF) with respect to critically overloaded branches or critical under/overvoltage buses. SOLS consider loads at these buses as control variables and then computes the optimal value of the load to shed using an SCM solver. Shed value of the load at the target buses can be anywhere between 0% and 100%.

For comparison, the modified SCM problem is then solved with three objective functions: minimizing fuel cost (“F”), losses (“L”), and disconnected load (“DL”), in order to provide the optimal operating point with zero security constraint violations.

7.2.5.4 Remedial Action – Demand Side Management

Similarly, the network operator may activate DSM on all or some of the buses, based on previous knowledge, priority, and size of the loads. In general, major industrial consumers will distribute their load into “essential”, “semi-essential” and “non-essential” categories (this statement has been made based on the author's experience of working with major industrial consumers). The non-essential load will be around 30% of the total demand, which can be employed as a manageable demand as and when required by the grid. Accordingly, the same approach for load shedding using the OLS and SOLS is applied for DSM, but the DSM analysis assumes that up to 30% of the load at target buses is available without (significant) impact on customers.

7.2.5.5 Dynamic Simulation of Remedial Actions

A remedial action results in a secure system if and only if the steady state security constraints are satisfied at post-control-action state (i.e. post-disturbance state after the implementation of remedial action) and the dynamic security constraints during the transition from pre-control-action (i.e. post-disturbance state before implementation of remedial action) to post-control-action state. Assuming proper controls are included in the mathematical formulation of SCM and that the formulation is feasible, the resulting solution provides a future (post-control-action) equilibrium operating point which is secure only from the steady security viewpoint.

However, following the activation of the remedial action suggested by the SCM analysis, the system may or may not reach the new operating equilibrium based on the severity of the disturbance and the dynamic response of various equipment to the implemented controls. In order to check the ability of the system in reaching the new operating equilibrium, a full time-domain simulation between pre-control-action to the post-control-action state should be carried out. Time domain simulations verify the satisfiability or non-satisfiability of dynamic security or stability constraints for a steady-state secure operating point. It should be noted that time-domain simulation should be executed only after the confirmation that there exists a steady-state secure operating point (i.e. through SCM analysis) with the considered remedial action. If no such steady-state operating point exists, there is no point in performing time domain simulation.

Time domain simulations are performed using [156] for a total duration of 60 sec, with the following steps: a) base case OPF on the pre-contingency network is run for the first 10 sec, b) the first and second line outages are simulated at 10 sec and 15 sec, c) remedial actions (e.g. SOLs) are activated at 20 sec, d) generation and voltage set points are readjusted at 25 sec and simulation is run until 60 sec with no further events.

The considered remedial action is “rotor angle stable” if and only if relative angles of all generators reached steady-state values and are within the margin of $\pm 180^0$. If a relative rotor angle exceeds $\pm 180^0$, that generator is assumed to lose synchronism with the rest of the system. Similarly, the selected remedial action is assumed to be "voltage stable" if the terminal voltages of all generators reached their steady-state values and none of them was outside the 0.95 p.u. - 1.1 p.u. range.

7.3. Results

7.3.1 Analysis of Post-Contingency Operating Conditions

Four overstressed SCM test cases (Table 7.1) are used to demonstrate the proposed remedial action framework. These cases are developed by simulating infeasible contingencies at pre-contingency optimal operating point. These cases develop overstressed operating conditions in two test networks (IEEE 30 and IEEE 57-bus), which are already validated in Chapter-4 (Table 4.4). Post-contingency operating conditions, following these infeasible contingencies, are analysed and the list of immediate post-contingency constraints is shown in Table 7.1. Where NUV, NOV and NOL indicate the number of under and overvoltage violations, and overloads; and TNSCV indicates the total number of security constraint violations. The type, extent, and severity of constraint violations vary by the chosen contingency.

Table 7.1 List of Analysed Test Cases with Immediate Post-Contingency Violations

Test Case	Contingency	Network	NUV	NOV	NOL	TNSCV
IC3	L1-2 & T27-28	IEEE 30	4	0	5	9
IC4	L4-12 & T27-28	IEEE 30	5	0	3	8
IC5	L5-6 & L6-7	IEEE 39	3	0	6	9
IC6	L21-22 & L26-27	IEEE 39	0	3	4	7
IC7	T7-29 & L8-9	IEEE 57	35	0	5	40
IC8	T7-29 & L46-47	IEEE 57	18	1	1	20

Note: Lx-y: Line between bus x and busy; Tx-y: Transformer between bus x and y

7.3.2 Computation of Non-Emergency Corrective Control Solution

Here, the relevant SCM problem is formulated and solved using a conventional solver (PSSE) to compute a possible NECC solution that can resolve all post-contingency constraint violations (Table 7.2). The NECC considered here are: generation re-dispatch, AVR set points, and tap settings. As the considered cases are infeasible, PSSE is failed to compute an NECC solution. Furthermore, the nonexistence of NECC solution is confirmed by IDRF.

Table 7.2 Existence Status of NECC solution

Test Case	Network	Existence of an NECC solution	
		By PSSE	By IDRF
IC3	IEEE 30	X	C
IC4	IEEE 30	X	C
IC5	IEEE 39	X	C
IC6	IEEE 39	X	C
IC7	IEEE 57	X	C
IC8	IEEE 57	X	C

X- Solver failure to compute solution; C – Confirmation of no solution

7.3.3 Identification of CCVs

The infeasible SCM problem formulated in the previous section is forwarded to CRF in order to identify the CCVs. It should be noted this study is already been done in Chapter-6, and list of CCVs are mentioned in Table 7.3. It can be seen that a large number of immediate post-contingency constraint violations reduce to a much smaller set of CCVs (most notably for the IEEE-57 system). Although the computational time varies depending on the size of the network and level of stress, it is observed that the average computational time to identify CCVs is around 40 sec.

Table 7.3 List and locations of CCVs

Contingency	Network	NUV	NOV	NOL	UV Buses	OL Lines	Time(s)
IC3	IEEE 30	2	0	2	29;30	33(L22-24); 35(L24-25)	14.34
IC4	IEEE 30	2	0	2	29;30	33(L22-24); 35(L24-25)	21.32
IC5	IEEE 39	0	0	2	/	3((L2-3); 9(L4-14)	36.04
IC6	IEEE 39	0	0	1	/	3((L2-3)	9.13
IC7	IEEE 57	6	0	0	24;27;28;29;52;53	/	76.34
IC8	IEEE 57	6	0	0	24;27;28;29;52;53	/	70.54

7.3.4 Computation and Implementation of Remedial Actions

This section presents the results to demonstrate the computation and optimal implementation of proposed remedial actions. The analysed remedial actions are: distributed generation (DG) dispatch, reactive power control, load shedding, and demand-side-management (DSM). In addition, this section also presents the results for the stability analysis of remedial actions. One metaheuristic solver (modified PSO, introduced in Chapter -3) and one conventional solver (an interior point OPF solver, PSSE, from [155]) are used for the analysis.

7.3.4.1 Load Shedding

The load shedding approach is applied to the IEEE 30-bus network as this has a mixture of thermal and voltage CCVs. Branches L22-24 and L24-25 are the most critical branches, the security constraints of which cannot be fulfilled without shedding load at some selected or target buses (Table 7.3). Table 7.4 shows that the PISFs for these critical branches are the highest at buses 29 and 30, indicating that they significantly influence the MVA flow in the critical branches. For example, for the outage of IC3 (L1-2 and T27-28), the injection of one MW at bus 29 reduces the flows on L22-24 and L24-25 by 0.811 MVA and 1.168 MVA, respectively. Based on this logic, bus 29 and bus 30 are considered as the target buses for SOLS (Table 7.5). The target buses for the HLS and OLS approaches include buses 29 and 30 as well as 4 other locations associated with immediate post-contingency constraint violations (from unconstrained power flow) as indicated in Table 7.5.

The total disconnected MVA for the 30-bus network with minimized objectives of fuel cost, loss, and disconnected load are shown in Table 7.6 with the resulting objective values shown in Table 7.7. The tables refer to “PSSE” and “PSO” which show the outcomes of conducting the SCM with conventional and metaheuristic approaches. These are included to demonstrate that the approach can be used with either method (where possible) and to indicate any differences in performance. In most cases of load shedding and SCM objective, the PSSE and PSO disconnection volumes and objective values are the same or very close. The obvious differences arise with the minimum load shedding objective, where the PSO substantially outperforms the conventional approach. The largest difference is for the first contingency where the reduction in load shedding is 77% for the SOLS and 90% for OLS methods. In addition, the SOLS approach results in much lower levels of load shedding compared to the other methods. Similarly, load shedding analysis is carried out for 39-bus and the resulting disconnected MVA are shown in Table 7.8.

Table 7.4 Active Power Injection Sensitivity Factors for IEEE 30-Bus

ISFs with outages of L1-2 and T27-28						
Branch\bus No	B24	B25	B26	B27	B29	B30
L22-24	-0.696	-0.752	-0.769	-0.781	-0.811	-0.831 [a]
L24-25	0.000	-1.089	-1.112	-1.129	-1.168	-1.196
ISFs with outages of L4-12 and T27-28						
Branch\bus No	B24	B25	B26	B27	B29	B30
L22-24	-0.801	-0.868	-0.887	-0.903	-0.937	-0.962
L24-25	0.000	-1.086	-1.109	-1.126	-1.167	-1.195

[a]Buses with high absolute ISFs

Table 7.5 Target Buses for Load Shedding

Conti.	SOLS	OLS	HLS
IEEE 30-bus			
L1-2&T27-28	29, 30	3, 4, 24, 26, 29, 30	3, 4, 24, 26, 29, 30
L4-12&T27-28	29, 30	3, 4, 24, 26, 29, 30	3, 4, 24, 26, 29, 30

Table 7.6 Total Disconnected MVA with Load Shedding (IEEE 30-Bus)

IC3: L1-2 and T27-28						
Type of shed->	SOLS		OLS		HLS	
Objective	PSO	PSSE	PSO	PSSE	PSO	PSSE
Min. Fuel cost	13.33	13.33	38.95	38.95	38.95	38.95
Min. Active Loss	13.32	13.33	34.93	38.95	38.95	38.95
Min. Shedding	3.07	13.33	3.93	38.95	NA	NA
IC4: L4-12 and T27-28						
Type of shed->	SOLS		OLS		HLS	
Objective	PSO	PSSE	PSO	PSSE	PSO	PSSE
Min. Fuel cost	13.33	13.33	38.95	38.95	38.95	38.95
Min. Active Loss	13.33	13.33	37.38	38.95	38.95	38.95
Min. Shedding	7.05	13.33	7.29	23.12	NA	NA [1]

[1]Not Applicable

Table 7.7 Optimal Objective Values with Load Shedding (IEEE 30-bus)

IC3: L1-2 and T27-28						
Type of shed->	SOLS		OLS		HLS	
Objective	PSO	PSSE	PSO	PSSE	PSO	PSSE
Fuel cost ($/hr)	787.27	787.54	703.29	703.48	703.22	703.48
Active Loss (MW)	3.17	11.50	2.90	11.34	2.68	11.34
Min Shed (MW)	2.92	13.00	3.32	15.63	NA	NA
IC4: L4-12 and T27-28						
Type of shed->	SOLS		OLS		HLS	
Objective	PSO	PSSE	PSO	PSSE	PSO	PSSE
Fuel cost ($/hr)	756.14	756.38	677.00	677.33	694.97	677.32
Active Loss (MW)	2.57	8.66	1.91	7.72	3.88	7.71
Min Shed (MW)	6.83	12.89	6.71	14.45	NA	NA

Table 7.8 Total Disconnected MVA with Load Shedding (IEEE 39-Bus)

IC5: L5-6 and L6-7						
Type of shed->	SOLS		OLS		HLS	
Objective	PSO	PSSE	PSO	PSSE	PSO	PSSE
Min. Fuel cost	502.34	532.78	1055.64	1332.28	1332.28	1332.28
Min. Active Loss	494.43	532.78	1077.72	1107.12	1332.28	1332.28
Min. Shedding	452.23	532.78	497.83	754.07	NA	NA
IC6: L21-22 and L26-27						
Type of shed->	SOLS		OLS		HLS	
Objective	PSO	PSSE	PSO	PSSE	PSO	PSSE
Min. Fuel cost	523.10	532.78	1021.55	1605.18	1605.18	1605.18
Min. Active Loss	515.74	532.57	847.12	842.72	1605.18	1605.18
Min. Shedding	443.51	450.73	480.41	471.92	NA	NA1

The branch MVA flows before and after the load shedding are shown in Figure 7.2. This demonstrates that, while SCM analysis with only NECC (i.e. SCM with no load shedding) can reduce five thermal constraint violations to two (denoted as critical overloading in Figure 7.2), SCM analysis with remedial action (i.e. SCM with HLS, OLS, and SOLS) can alleviate all thermal constraint violations.

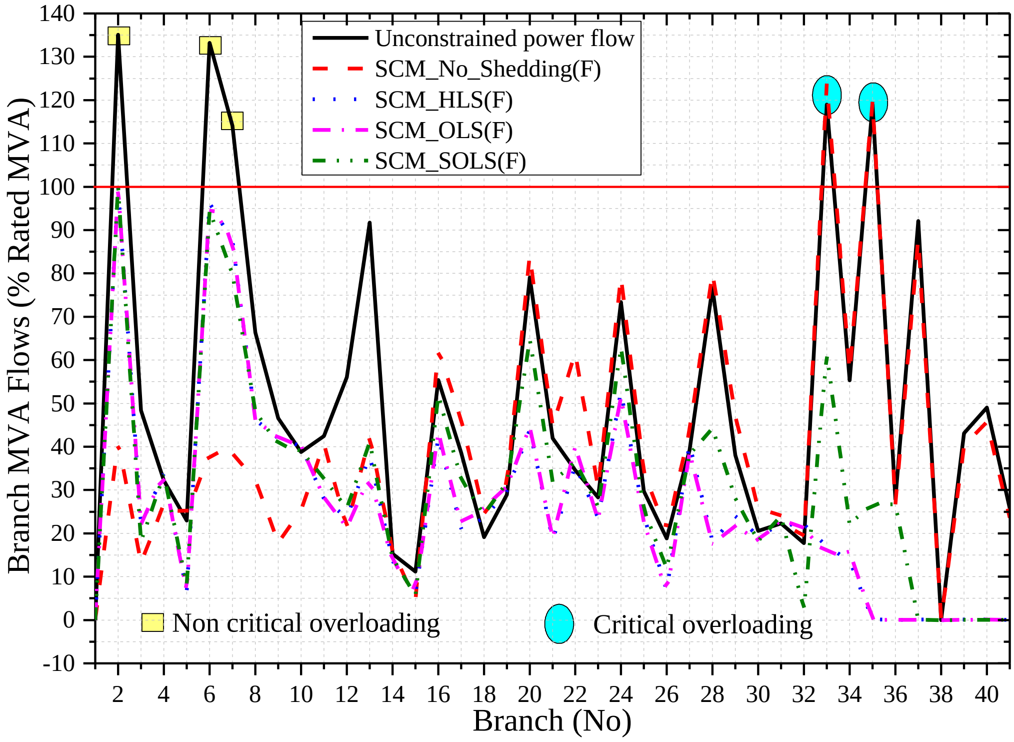


Figure 7.2 Branch MVA flow with load shedding for IEEE 30-bus (IC3)

7.3.4.2 Demand side management

The same process used for load shedding was repeated for DSM with the OLS and SOLS approaches (denoted as OLS-DSM and SOLS-DSM in the Tables and Figures). The target buses for OLS- and SOLS-based DSM are identified based on PISFs for the critical branches (Table 7.5). The resulting disconnected load volumes (MVA) with DSM based OLS and SOLS are shown in Table 7.9. Once again, the SOLS approach is better than the OLS in all cases, and in some instances substantially outperforms it. The conventional and metaheuristic outcomes are similar in most cases, but PSO performs better for the load shedding objective.

The convergence of the PSO solver for one contingency (IC4) is shown in Figure 7.3 for both OLS and SOLS cases for each of the objectives. This tracks how the total number of security constraint violations fall as the iterations progress. In all cases, the zero-security constraint violation in the figure indicates that all security constraints are fulfilled but that there is some variation in the speed at which this is achieved. All cases see a very rapid reduction in violations in the early stages before more steady progress. The OLS approach for minimizing fuel cost reaches zero violations most rapidly but it should be noted that this case has the highest amount of load shedding. This suggests there may be a degree of trade-off between speed and efficacy.

Table 7.9 Total Disconnected MVA with SOLS-DSM and OLS-DSM

IC3: L1-2 and T27-28				
Type of shed->	SOLS		OLS	
Objective	PSO	PSSE	PSO	PSSE
Min. Fuel cost	4.00	4.00	11.68	11.69
Min. Active Loss	4.00	4.00	9.86	11.69
Min. Shedding	2.99	4.00	3.38	11.69
IC4: L4-12 and T27-28				
Type of shed->	SOLS		OLS	
Objective	PSO	PSSE	PSO	PSSE
Min. Fuel cost	8.55	8.55	11.68	11.69
Min. Active Loss	8.55	8.55	11.64	11.66
Min. Shedding	7.72	8.55	4.18	8.81

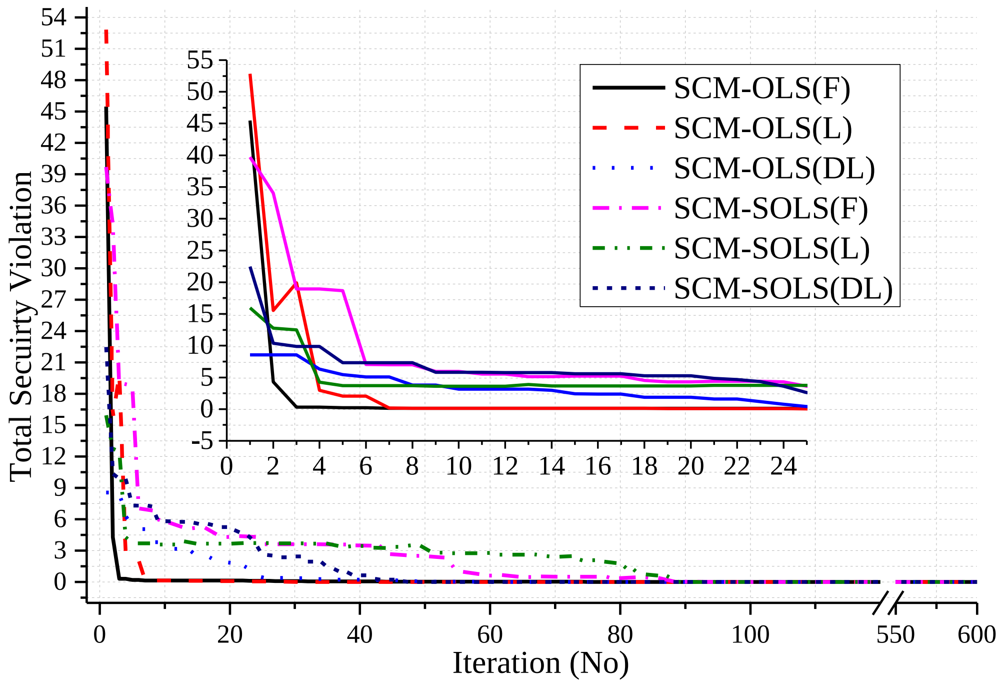


Figure 7.3 Total number of security violations with iteration of the PSO (IC4)

7.3.4.3 Optimal Control of Distributed Generation (DG)

The use of DG dispatch is demonstrated using the IEEE 30-bus system whose critical thermal constraints (L22-24 and L24-25) cannot be fulfilled without the injection of active power. The bus PISFs for those critical branches are presented in Table 7.4 and buses 29 and 30 are again the target buses for DG placement and control. The DG are both considered as 5MW units capable of being dispatched from zero to maximum. Their fuel cost is modelled as a polynomial with the following equations: $0.02P_g + 15$ at bus 29 and $0.043P_g + 20$ at bus 30. The DGs are assumed to provide only active power. The characteristics of the other generators in the system remain unchanged.

The system is dispatched with either minimum fuel cost or loss objectives for each set of contingencies (IC3 & IC4). The results (Table 7.10) show the loading of the existing conventional generators and the two DG. The outcomes of the conventional and metaheuristic algorithms are broadly similar. However, the dispatch to meet the fuel cost objective is quite different to that of minimal losses and much greater use is made of the DG at bus 30 in minimizing losses. In addition, it is also observed that the post-contingency dispatch of conventional generators is significantly changed from the pre-contingency dispatch which indicates that the system operating point has moved quite far away from the pre-contingency optimal operating point.

The branch MVA flows for one contingency (IC3) before and after DG dispatch are shown in Figure 7.4. As all the branch constraint violations are relieved after the introduction of DG, it suggests that knowledge of the locations of critical constraints makes DG effective in alleviating line and voltage congestion, irrespective of the objective function considered. DG does not necessarily need to be located at the critical branches to be effective. For example, the target buses (bus 29 and 30) in this study are not associated with the critical branches (L22-24 and L24-25), Table 7.3.

Table 7.10 Optimal DG Dispatch with relevant Objective Values

Gen	IC3: L1-2 and T27-28				IC4: L4-12 and T27-28			
@	OFC		Loss		OFC		Loss	
Bus No	PSSE	PSO	PSSE	PSO	PSSE	PSO	PSSE	PSO
1	130.0	129.72	50.00	53.04	158.79	150.34	50.01	57.24
2	63.37	63.62	77.03	77.00	44.32	46.61	71.35	78.90
5	25.29	25.18	49.38	50.00	20.00	17.88	49.99	50.00
8	35.00	32.09	34.92	34.62	11.03	13.71	34.98	34.91
11	21.00	21.38	29.94	30.00	10.01	15.42	29.98	20.11
13	16.58	18.90	35.13	33.13	40.00	40.00	39.97	36.27
29 (DG)	4.83	4.90	4.99	4.80	5.00	5.00	5.00	4.87
30 (DG)	0.00	0.15	5.00	4.99	2.52	2.58	5.00	4.86
Objective value	897.3 \$/hr	900.1 \$/hr	3.59 MW	4.24 MW	924.7 \$/hr	927.9 \$/hr	2.88 MW	3.78 MW

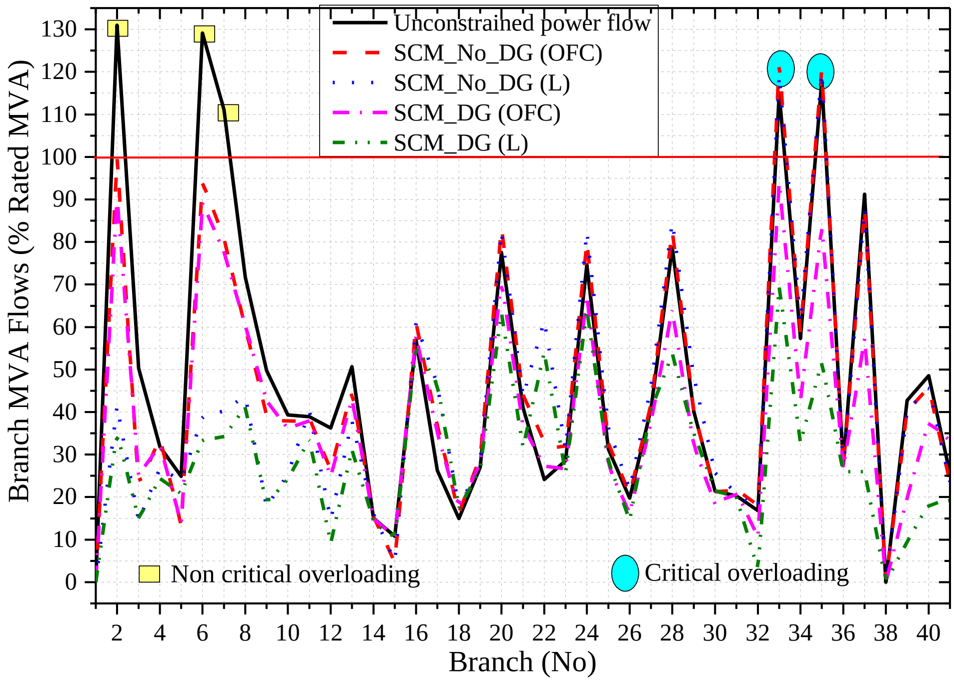


Figure 7.4 Branch MVA flow with load shedding for IEEE 30-bus (IC3)

7.3.4.4 Optimal Reactive Power Injection

Unlike the previous interventions, reactive power control is demonstrated on the IEEE 57-bus system as the CCVs include only undervoltage violations (Table 7.3) and the SCM is a VVC problem. Table 7.11 shows the extent of the undervoltages post-contingency (IC7) before the SCM dispatch with reactive support. These can be seen to be between 1 and almost 7 percentage points below the 95% undervoltage limit. Reactive support (capacitors) are available at each of the critical buses and the SCM run for the three objectives (fuel, losses and reactive injection). The resulting optimal reactive power injection values for one contingency (IC7) are shown in Table 7.12.

There are fairly similar overall volumes of reactive support and objectives between PSSE and the PSO for the fuel cost minimization case. The allocation of the injections between buses is quite different, however. For the loss minimization case, the PSO performs slightly worse than PSSE in terms of the amount of reactive support required overall and has almost twice the level of losses. The objective of minimizing reactive support sees a substantial reduction in volumes with the PSO and zero or near zero injections at two of the three locations. This would suggest PSO may be more efficient in terms of the number of capacitors used.

Table 7.11 Bus Undervoltages for IEEE 57 Bus (Below 0.95 pu limit)

Contingency	Bus undervoltages (%) with fuel cost min.					
	B24	B27	B28	B29	B52	B53
T7-29&L8-9	1.93	4.43	6.20	6.96	6.02	4.82
T7-29&L46-47	1.08	2.45	3.99	4.61	3.19	1.72
Contingency	Bus undervoltages (%) with loss min.					
	B24	B27	B28	B29	B52	B53
T7-29&L8-9	2.14	4.23	5.97	6.71	5.72	4.49
T7-29&L46-47	1.80	3.46	5.09	5.75	4.49	3.12

Table 7.12 Optimal Reactive Power Injection with relevant Objective Values (IC7)

Objective->	With minimized Fuel cost		With minimized loss		With minimized shunt	
Bus No	PSSE	PSO	PSSE	PSO	PSSE	PSO
B24	7.58	3.60	3.05	4.71	2.87	0.03
B27	2.63	7.14	4.09	1.84	3.67	1.17
B28	2.45	2.57	4.30	4.76	3.63	4.23
B29	2.53	3.97	4.36	6.82	3.58	3.95
B52	2.39	1.02	3.80	1.30	3.38	5.90
B53	5.54	4.75	3.38	4.73	3.09	0.00
Total MVAr	23.12	23.05	22.98	24.16	20.20	15.28
Objective value	44757.5 $/hr	44861.0 $/hr	14.82 MW	28.59 MW	20.20 MVAr	15.28 MVAr

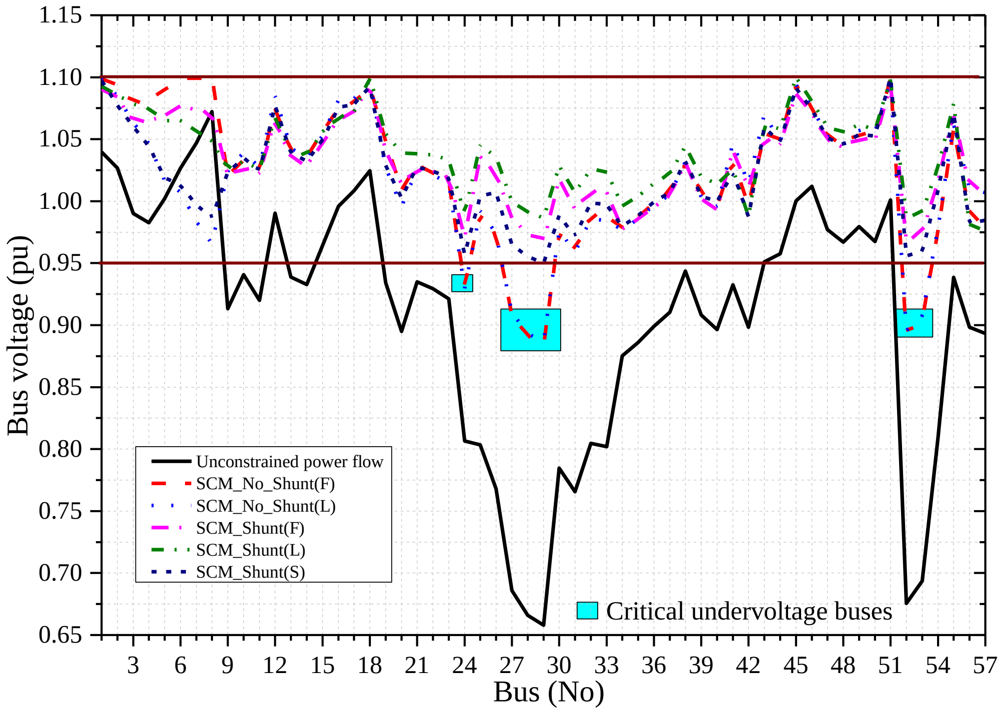


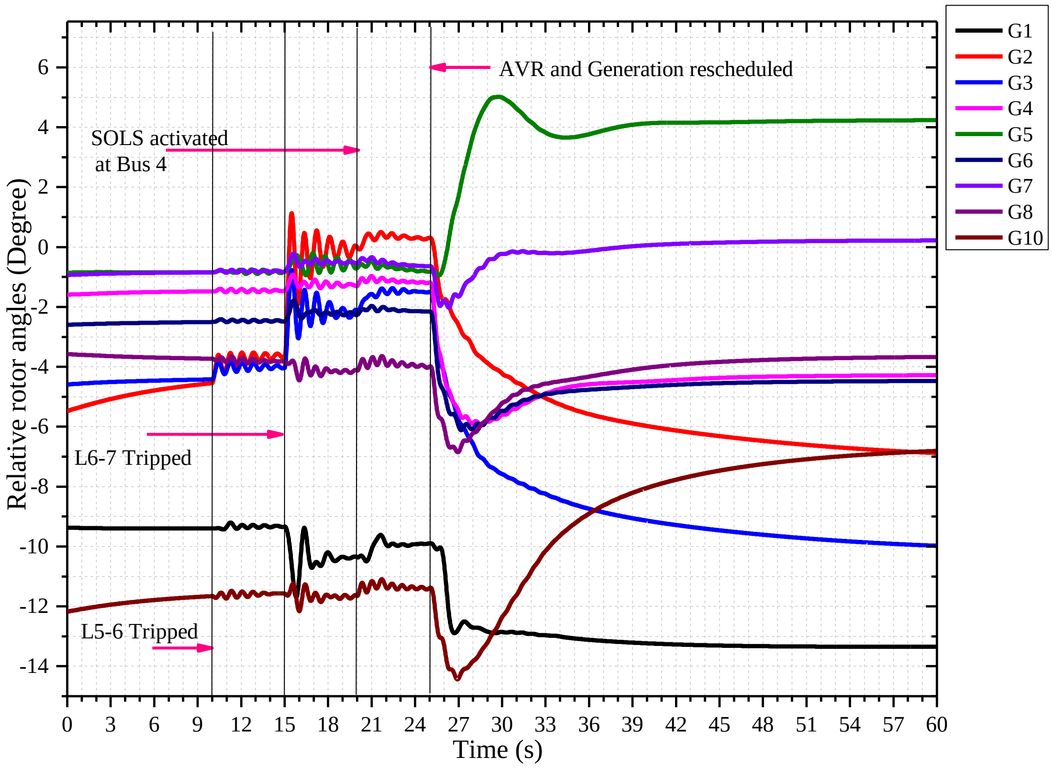
Figure 7.5 Voltage profile for 57-bus system with and without reactive support (IC7)

The effect of the reactive support is clearly visible in Figure 7.5 for contingency T7-29 and L8-9 before and after the reactive injection. While the post-contingency, unconstrained power flow represents 35 undervoltage violations, the approach suggests reactive power injections at only six buses will fulfil those undervoltage violations. Hence, the presented approach requires reactive injection at a minimum number of buses which, in turn, minimises switching actions.

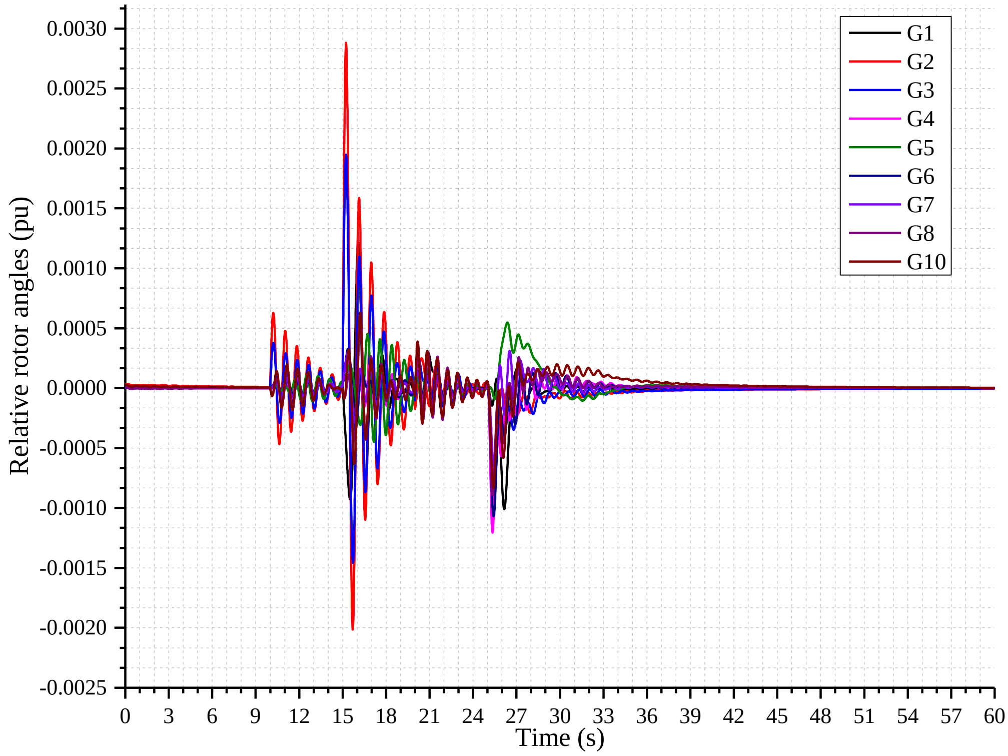
7.3.4.5 Dynamic Security Validation of Remedial Actions

Time domain simulations of the transition from pre- to post-contingency steady state secure operating points is done for two reasons: a) to additionally check whether the system can reach new stable operating state, or not, and b) to check whether the presented remedial action framework does not result in any voltage or angle instability.

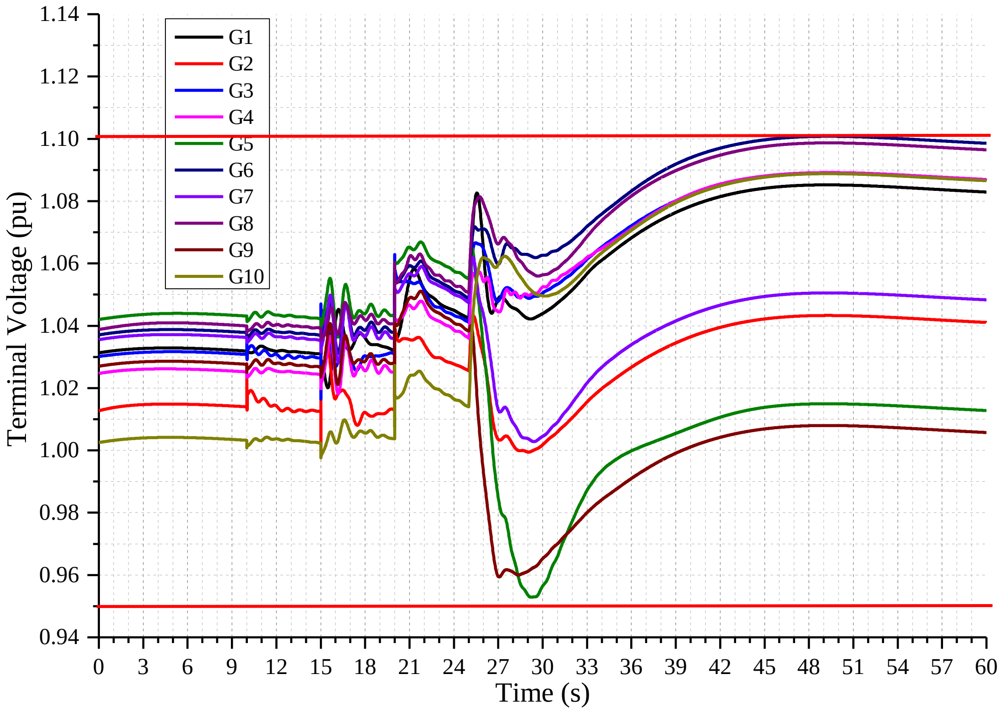
The results of dynamic simulations for generator terminal voltages, rotor angles and speeds for IEEE 39-bus network with the activation of SOLS following a double line contingency (IC5) are shown in Figure 7.6. It can be observed that all the relative rotor angles and speeds have reached steady state, and none of the relative rotor angles are exceeded $\pm 180^0$ margin (Generator G9 is considered as the reference machine). In addition, the terminal voltages of all the machines have reached steady state which are same as the AVR set points computed by the remedial action. This confirms that the proposed remedial action does not initiate any voltage and angle instability problems.



a) Relative rotor angles



b) Relative rotor speeds



c) Terminal voltages of generators

Figure 7.6 Dynamic stability simulations for generator terminal voltages, rotor angles and speeds for IEEE 39-bus network with the activation of SOLS following a double line contingency (IC5)

7.4. Discussion

It is widely accepted that the management of constraints can be a more economically efficient option than further investment in the transmission network [21]. Accordingly, system operators invest significantly in procuring various ancillary services (active and reactive power) to resolve constraint violations during overstressed and emergency operating conditions.

The proposed remedial action methodology incorporating the concept of critical constraint violations (CCVs) presents a useful unified computational framework to diagnose overstressed situations; and suggest a selection of effective remedial actions. These are based on CCV classification and effective implementation using injection sensitivity factors to minimize the usage of system reserves (for economic operation) as well as required number of switching actions (for secure transition from pre- to post-disturbance steady-state equilibriums). This contribution can be demonstrated from the following observations.

Although there are differences in disconnected load, DG value, and capacitor values with various objective functions, all the proposed remedial actions find the secure post-disturbance operating point with zero constraint violations.

The proposed demand control approach (SOLS and SOLS-DSM) require smaller disconnection volumes at a minimum number of buses compared to the HOLS (activated by under-voltage or under-frequency protection at the local level) or OLS (activated by the operator using computer controls over the regulated region). Taking advantage of adaptive relays, the protection settings of which can be changed in real time, SOLS can be integrated into existing protection systems.

The traditional undervoltage or under-frequency load shedding tends to shed the loads at the buses experiencing undervoltage or under-frequency (i.e. overloads) to prevent the network from entering the insecure region. However, from an economic and secure operation viewpoint, these buses may not be the most effective for constraint management in large and highly interconnected networks. This is evidenced by the implementation of SOLS in which the target buses for demand control are not the ones associated with overloaded branches.

The reactive compensation approach requires minimum reactive support at a minimum number of buses to alleviate voltage congestion. Hence, it can help reduce unwanted switching surges, voltage dips and swells, and the relevant consequences, which are often associated with the switching operation of capacitor banks.

The important point to reiterate about this approach is that it does not replace existing methods of handling challenging situations. Rather, in providing a computational means of identifying and classifying the CCVs it can extend the reach of support to system operators. The approach could form part of offline analyses and be offered as part of a lookup table or some form of case-based reasoning method. This method could conceivably be incorporated as part of online systems, as the straightforward manner in which the PSO solver can be parallelized means its elapsed time will be sufficiently short. This allows it to be broadly competitive with conventional methods requiring a few seconds to provide the solution. PSO needs only about 40 seconds (on average) to identify the CCVs and 30-100 seconds to compute the remedial action. But, once the CCVs identified, system operator can use conventional solvers to speed up the remedial action computation process.

For large practical systems, computational time can be reduced by employing inherent task-level parallelism at the objective function calculation stage and data level parallelism at the optimization stage. Furthermore, handling of a high number of constraints in metaheuristic algorithms can be addressed by developing domain-independent constraint handling approaches.

In addition to operational application, this approach can also be used during planning to indicate optimal location and sizing of DG, shunt capacitors, energy storage, etc. The remedial action framework can also be used for strategic (day ahead, weekly, or monthly) planning and invitation of potential bidders for ancillary services to minimize the investment. The repeated SCM analysis, for example, with severe contingent events over forecasted energy demand or various load distributions (using the Monte Carlo approach) can be used to plan various active and reactive power ancillary services for improved congestion management and volt-var control, respectively.

7.5. Conclusions

This chapter presented a remedial action framework for improved security constraint management to mitigate situations of network overstress. The practical relevance of the proposed framework is demonstrated on three widely used IEEE test networks and is of significant value to system operators (and potentially planners). From the optimization perspective, it can help resolve planners resolve infeasibility in optimization models by identifying the critical constraint violations and devising effective preventive actions. From the operational perspective, it eases the dynamic transition between pre- and post-contingency static equilibrium points (calculated from steady-state analysis) as it requires minimum switching actions to implement the remedial actions. By identifying the minimum number and extent of CCVs, i.e. by detecting critical alarms from a possibly larger number of activated post-contingency alarms, the presented framework can also help the system operators to deal with “alarm flooding”. By effectively handling the critical security constraints and allowing the network to operate at or near technical security limits, it offers potential to exploit unused (“hidden”) network capacity to host more renewable generation or to supply higher demands.

Chapter 8

Conclusions

8.1. Summary

Security constraint management (SCM) remains to play a critical role for the analysis of secure and stable operation of power supply systems. Arguably, SCM is more important than ever before, as modern electricity networks are more frequently operated closer to their technical limits, i.e. under stressed and even overstressed system operating conditions. The main aim of this thesis is development of improved and efficient approaches for the analysis and management of security constraints under overstressed system operating conditions. The summary of the work is given below.

Chapter 2 presented a theoretical background and discussed the importance of the SCM problem in modern electricity networks. It has defined the stressed and overstressed operating states, in aligning with the existing classification in the literature. It also explained that overstressed operating conditions can be approached and interpreted as infeasible mathematical formulations of the SCM problem.

Chapter 3 presented a detailed discussion of the mathematical formulation of the SCM problem and an in-depth analysis of feasible and infeasible SCM cases. It also provided an intuitive explanation of the computational processes behind the conventional and metaheuristic methods for solving the SCM problem. In order to resolve infeasible formulations, and in that way mitigate overstressed operating conditions, this chapter introduced two concepts: minimum intractable subsystem of constraints (MISC) and critical constraint set (CCS). While MISC represents a minimal set of constraints causing the infeasibility purely from a mathematical viewpoint, the CCS is defined as a set of the (most) critical constraints, whose violations prevent the operator from devising a feasible dispatch with available non-emergency corrective controls and for a given operational objective or control priority.

Chapter-4 has developed and validated a set of several feasible and infeasible SCM cases for several (standard) test networks. It has been proved that conventional nonlinear programming solvers were failed to analyse infeasible cases. In other words, they were failed to diagnose the MISC as well as failed to provide information on a set of problematic constraints (at least).

Chapter 5, employing a modified metaheuristic framework, has proposed an infeasibility diagnosis and resolution framework (IDRF). The framework was validated on several test networks and the obtained results prove that the proposed IDRF can reliably find the close representation of the MISC for all considered infeasible cases.

Chapter 6 has proposed a constraint rationalization framework (CRF) to resolve CCS based on five different operator's priorities: a) cost of available non-emergency corrective actions, b) allocated available computational time, c) pre-specified size of CCS, d) available reserves, and e) available time before the next contingency occurs. The framework was again validated with several infeasible cases and the obtained results demonstrate that the framework can successfully find the CCS in all considered cases.

Using IDRF and CRF, Chapter 7 has established a remedial action selection and implementation framework (RASIF). This framework has used the information on the type of constraints in CCS to select the best remedial action(s), and locations of constraints in CCS to find the most effective network locations to implement the selected remedial action(s). As before, the framework has been demonstrated on several test networks using both static and dynamic simulations. These results have shown that the implementation of suggested remedial actions requires minimal system reserves and minimum number of switching actions, when compared to the existing approaches.

8.2. Implications of the Presented Research

This thesis has provided numerous approaches, and required theoretical backgrounds, for dealing with overstressed operating conditions in modern electricity networks. The presented approaches effectively extend the state-of-the-art in security constraint management of modern power supply systems and are therefore expected to be of significant value to system operators and system planners. These approaches should improve the general decision-making capability of energy control centres in handling challenging situations, especially in the context of modern electricity networks. A detailed discussion of the research implications is presented below:

8.2.1 Definition and Detection of Overstressed Operating Conditions

The existing classification of system operating conditions have neither defined the stressed and overstressed operating conditions, nor said where exactly these conditions would fall within the existing framework. The previous definitions have not properly linked the stressed and overstressed system operating conditions into the existing classification of network operating points/states and did not provide a methodology to diagnose them. Traditional constraint management procedures were not associated with the specific tools that can differentiate between the stressed and overstressed operating conditions, as confirmed by the number of previous power system blackouts [51].

To address this gap, this thesis proposed a simple methodology to define and detect stressed and overstressed system operating conditions, based on the status of steady state security constraint violations. The methodology can be used by network operators for improved resolving of the overstressed operating conditions and for taking necessary mitigative actions. The prompt detection of overstressed conditions is particularly important, as in these conditions system is much more vulnerable to even small disturbances and as the probability of cascaded outages is significantly higher.

8.2.2 Analysis and Modification of Metaheuristic Approaches for Handling Infeasible SCM Formulations

While most of the previous research in metaheuristic optimization has entirely focussed on developing algorithms for finding accurate optimal solutions to feasible optimization problems, the analysis of infeasible optimization problems with metaheuristic approaches is not yet explored. This thesis, for the first time, has investigated the suitability of metaheuristic solvers for handling infeasible SCM models and for identifying, or as closely as possible representing the MISC. Accordingly, the thesis has proposed several modifications to the basic metaheuristic solvers, in order to improve their efficiency in finding/representing the MISC. From that perspective, this thesis has effectively opened a new research direction in metaheuristic optimization of infeasible models.

8.2.3 Test Cases for Validation of Infeasibility Diagnosis Techniques

Optimization models, especially SCM/OPF models, which are commonly used to make planning and operational decisions in modern electricity networks, are becoming progressively larger and more complex, due to increased network interconnections, renewable energy penetration, complex controls, and frequent operation under stressed and even overstressed conditions. As models continue to grow larger, they can more easily become infeasible and identifying and resolving these infeasibilities becomes increasingly difficult.

It is expected that there will be an increased research interest in devising new techniques to diagnose infeasibility in SCM/OPF models in the future. It is, therefore, very important to diagnose and localize the infeasibility, not only to resolve it from the optimization viewpoint, but also to identify parts of the electricity transmission and distribution networks ("bottlenecks") where additional reinforcement and upgrading are required, or additional system support services should be contracted, so that non-emergency and emergency corrective actions can be devised in the most cost-effective ways to deal with the constraint violations.

This thesis has developed and validated several infeasible SCM cases with widely used test networks, so researchers can both select and validate the most suitable approach from the presented infeasibility diagnosis techniques and approaches. These cases exactly represent the overstressed operating conditions for several test networks. Moreover, on a wider scale, these cases could serve as general infeasible optimization models, so that researchers from any field can use them. By providing a set of validated infeasible models, this thesis may help scientific community in progressing research in a general field of infeasibility diagnosis. In addition to infeasibility diagnosis, these test cases can also be useful for the researchers aiming to devise remedial actions for resolving overstressed system operating conditions.

8.2.4 Infeasibility Diagnosis and Resolution Framework for SCM

Building on a modified metaheuristic framework, this thesis has developed a novel infeasibility diagnosis and resolution framework (IDRF) for nonlinear SCM models. Existing commercial OPF programmes, which typically rely on conventional solvers, are unable to diagnose the infeasibility in nonlinear SCM models and the information they return in these cases is not of much use to the engineers and operators for resolving the infeasible models.

Essentially, the mathematical indication of infeasibility is related to specific practical conditions that are important for a secure system operation, and any further attempt to operate the network under these conditions might result in the further activation of protection systems, or in angle/voltage instability. Especially when the system is overstressed, ability to quickly identify the root causes of the infeasibility (i.e. MISC) is more important than solving the OPF/SCM problem in its original or relaxed forms.

In this context, the proposed IDRF framework could be used by engineers and network operators for efficient handling and resolving of infeasible SCM models, as and when they arise, as demonstrated by considering several infeasible SCM cases. Essentially, the presented frameworks can be easily implemented as an additional functionality (or computational routine) in commercial OPF software, where the information on the estimated MISC can guide conventional solvers whenever they diverge or fail to converge.

8.2.5 Constraint Rationalization Framework for Overstressed Operating Conditions

The accurate identification of types and locations of critical constraints is very important for the resolution of overstressed conditions, as the violations of these constraints prevents operator to devise a feasible re-dispatch of generation and adjustment of other controls. While the types of critical constraints help operators in deciding what types of remedial actions should be selected, the locations of critical constraints help operators to identify where and how to optimally implement these remedial actions, so that network can safely transit to a new secure operating state, without violating any dynamic security constraints during the transition.

This thesis, to the best of authors' knowledge, is the first to propose a constraint rationalization framework (CRF) for identifying the types and locations of critical constraints during overstressed operating conditions. The most important feature of this framework is that it acknowledges that the "criticality" of a constraint violation may vary based on the operator's evaluation and prioritization of post-contingency controls and actions. The proposed CRF enables the operator to identify the CCS, according to the previously discussed five different types of operator's priorities, but this framework can be easily extended to include other priorities, which an ISO may want to consider (e.g. minimization of the number of corrective actions in post-contingency state).

The potential of the presented framework was demonstrated with several overstressed study cases in considered test networks. The framework does not require any additional hardware and, hence, it could be implemented as an add-on computational tool to the existing energy management software (EMS) in energy control centres in a straightforward manner. Additionally, the outcome of CRF can be linked to the remedial action schedule/routine within the EMS, to activate only the specific remedial actions, which are deemed appropriate in dealing with particular overstressed conditions. Operators can enable or disable the CRF, as and when required, e.g. when linking it to a day-ahead planning tool to identify the critical constraints that may appear within the next 24 hours with the forecasted demand and committed generation.

In conclusion, if implemented in energy controls centres, the presented framework could significantly improve decision-making capability, as well the confidence levels of operators, in taking specific actions to mitigate the consequences of overstressed operating conditions. For example, an operator typically cannot process more than five alarms at a time and the proposed CRF could pinpoint the critical alarms, so that operator can devise most efficient decisions quickly. In the worst case, if the load shedding inevitable, the presented CRF can help in ensuring that the lowest amount of load is shed, as well as where exactly this load is to be shed.

8.2.6 Remedial Action Selection and Implementation Framework

After introducing CRF and IDRF, this thesis also proposed a remedial action selection and implementation framework (RASIF) to resolve or mitigate overstressed system operating conditions. The framework uses information on the types of constraints in CCS to select the proper remedial actions, where the most influential buses are selected as the most effective ones for the implementation of the selected remedial actions. The RASIF considers selected SCM problem as a vol-var control problem if CCS involves only voltage violations, and as congestion management problem if CCS involves a combination of line overloads and bus voltage violations, or just line overloads.

Based on the location and amount of available emergency reserves in relation to the type of SCM problem, the framework shows how to select minimal emergency reserves to fully resolve, or at least to limit the consequences of overstressed operating conditions. The most important feature of this approach is that it verifies the satisfiability of both steady state and dynamic security constraints. First, it finds the best emergency corrective solution that satisfies all steady state security constraints. Afterwards, if and only if all steady-state constraints are fulfilled at the post-corrective state, the framework proceeds further to verify that the transition to that post-corrective steady state secure state is possible by checking the dynamic security constraints via full-time domain simulations.

The practical relevance of the proposed framework is demonstrated on widely used test networks and is deemed to be of significant value to system operators and system planners. Unlike the event-based remedial actions, RASIF devises actions based on the evaluated system response, or system state in relation to the level of system stress. Hence, the remedial actions devised using this framework require minimal amount of system reserves and minimal number of switching actions. After a careful tuning, the framework can be linked with the on-line automatic control system in energy control centres, to automatically issue the most optimal remedial action commands to the target buses through the SCADA system. Moreover, RASIF with CRF can be integrated into the day-ahead operational planning tools, to plan ahead any remedial actions against any overstressed operating conditions that may appear in the next 24 hours. In addition to all that, by effectively handling the critical security constraints and allowing the network to be operated at, or near technical security limits, the presented framework has potential for further exploitation of the unused ("hidden") network capacities, e.g. to host more renewable generation, or to supply higher demands.

In conclusion, to the best of author's knowledge, this thesis is the very first methodological attempt at analysing, modelling and resolving the overstressed system operating conditions using mathematical formulations of infeasibility, where infeasibility diagnosis is used to identify critical constraints in terms of different operator's priorities. After doing that, the framework then implements the corresponding optimal remedial actions, based on the types and locations of critical constraints. The important feature of the proposed frameworks is that they do not intend to replace the existing approaches for managing security constraints during overstressed operating conditions. Rather, in providing the computational means of identifying CCS and devising remedial actions, the frameworks can extend the reach of available support to system operators.

8.3. Limitations of the Research

8.3.1 Computational Time

One of the inherent characteristics of the proposed frameworks, which might be considered as a "downside", is that they rely on metaheuristic solvers, which take (much) longer computational time than conventional solvers. However, it should be noted that in the most, if not all of the considered overstressed/infeasible cases, the conventional solvers were unable to diagnose the infeasibility (they effectively "detect" infeasibility by not converging, or diverging, but do not provide any useful qualitative or quantitative information about infeasibility), but metaheuristic solvers can. On average, the proposed frameworks need only about 40 seconds (for considered test networks and on a standard desktop PC) to diagnose the infeasibility and to identify the CCS, and then around 30-100 seconds to select and compute the remedial actions. Nevertheless, the estimated 40 seconds of computational time for considered networks is completely feasible for offline applications and reasonable for online applications and once the CCS are identified, the system operator can use conventional solvers to speed up the overall computation process

At present, the proposed frameworks and metaheuristic solvers were implemented entirely in Matlab environment, so it is inferred that the computational performance of the presented frameworks can be improved by implementing and optimizing them in C++ or FORTRAN (as in commercial OPF solvers), which, as discussed in the thesis, are much faster than the Matlab compiler [200]-[201]. Moreover, computational times can be further reduced by exploring inherent task-level parallelism at the objective function calculation stage, as well as data-level parallelism at the optimization stage. This would then allow metaheuristics solvers to be broadly much more competitive to conventional solvers, e.g. requiring only a few seconds to provide the target optimal solution.

8.3.2 Applicability to Practical Networks

The proposed frameworks were tested on a relatively small number of different test networks, with only up to 300 buses, and they have to be tested on more realistic networks of larger sizes, as well as on practical networks. Nevertheless, the author is of the opinion that the proposed frameworks, in their present form, can be applied directly to real transmission networks of similar size, e.g. New Zealand transmission network, or a network covered by a single TSO.

8.4. Recommendations for Future Work

This PhD research ("journey") has given me an opportunity to go through some fundamental research problems in power systems engineering, as well as in optimization theory. At the end of this research, I would like to offer my thoughts on some prudent and promising lines of research (amongst many other that I have contemplated), which are broadly related to this thesis and, to the best of my knowledge, yet to be pursued.

I strongly believe that the work presented in this thesis can be applied to several other problems in power systems engineering, as well as other fields: the IRDF and CRF have potential for applications to any optimization problem and some of the relevant research directions are mentioned below.

8.4.1. Infeasibility Diagnosis with Conventional Approaches

As mentioned earlier in the thesis, infeasibility diagnosis, and especially the identification of MISC, is an NP-hard optimization problem. There exists no reliable technique for conventional solvers to identify the exact, or even approximate MISC, in non-convex nonlinear infeasible optimization problems, and this is one of the challenging research fields to work on. Any improvement in this field could be of significant use to both the scientific community and industry. This thesis is one such attempt to identify the MISC, but it relies on metaheuristic solvers, and future research can focus on developing more efficient techniques for conventional solvers, in addition to metaheuristic solvers to diagnose the infeasibility.

8.4.2. Infeasibility Handling in Security Constrained Economic Dispatch (SCED)

If unit commitment solution after the market clearance cannot satisfy all (relevant) security constraints, SCED problem becomes infeasible and then market operators employ out-of-market corrections to make the system feasible. These out-of-market corrections basically involve constraint relaxation through fixed penalty prices, which requires additional generators to be committed/dispatched [203]. Accordingly, one can research the application of the proposed IDRF (or similar tools) to derive the exact amount of constraint relaxation, or penalisation values for resolving only the critical constraints. This approach may require fewer out-of-marker corrections (and therefore committing fewer generators) than the existing procedures, hence reducing the volatility in prices after the market clearance.

8.4.3. Detecting Cyber-Attacks from Known Disturbances

If an accurate system model is available, differences in actual system response from the simulated response can be modelled as an optimization problem. If both responses closely match, it could be inferred that the system is running normally and that there is no system fault or cyber-attack on the system. If the actual response does not match the simulated response, the actual response could be further checked against several simulated responses, each representing a known system disturbance. The set of known disturbances includes all possible system faults and cyber-attacks (which should be available from both historical records and previously simulated cases). If the actual response does not match one of the physical system faults or disturbances but matches some of the previously known cyber-attacks or if that disturbance actually did not take place in the system, it could be inferred that the system is likely under cyber-attack.

8.4.4. Rationalization of Alarm “Flooding”

One of the challenging problems in process industries is to identify the critical alarms amongst a larger number of activated alarms (e.g. more than ten alarms) during process emergencies, which is known as “alarm flooding”. One can model this problem as an infeasible optimization model and identify critical alarms by using approaches for handling the infeasibility similar to these presented in this thesis.

8.4.5. Infeasibility Handling in Engineering Design and Scheduling Problems

The application of IDRF to engineering design and scheduling problems can also be further researched, in order to identify the critical design requirements that cannot be satisfied, or are very difficult to satisfy. An example would be identification of "critical paths" that cannot be covered in case of flight scheduling problems.

8.4.6. Extending the General Capabilities of the CRF

The general capabilities of the CRF can be enhanced or extended by including other control priorities of the operators. For example, the operator might be interested in finding CCS with reduced number of controls, or with specific set/combination of controls in post-contingency state, or with only a minimum number of control adjustment actions (e.g. on/off switching) during the transition to a secure state, or to unconditionally preserve supply to specific/emergency loads, etc.

8.4.7. Extending the General Capabilities of the RASIF

The general capabilities of the RASIF can be enhanced or extended by including other corrective controls, for example transmission switching, energy storage, etc. One can also research the application of RASIF for strategic (day-ahead, weekly, or monthly) planning and subsequent invitation or incentivising of potential bidders for specific ancillary services to minimize the overall cost of system reserves. The repeated security constraint management analysis, for example, with severe contingency events over forecasted energy demand, or for various load distributions (using the Monte Carlo approach) can be used to plan various active and reactive power ancillary services aimed at improving congestion management and volt-var control, respectively.

8.4.8. Integrated Assessment of Static and Dynamic Security Assessment

The system stability in modern electricity networks is becoming more sensitive to even small disturbances due to continuously reducing inertia and damping levels. Hence, the dynamic security assessment is going to play a critical role than ever before. In this context, future research could be concentrated on three following directions.

First, in most of the previous literature, the employed dynamic assessment procedures did not pay much attention to the satisfiability of steady state security constraints at pre- and post-application of any corrective control. As mentioned previously, a corrective action can be dynamically secure (i.e. the transition is secure) but the post-control equilibrium state may be statistically in secure. Future research should be focused on the combined assessment of static and dynamic security.

Second, mathematical models representing the operation of modern electricity networks are becoming involved with non-smooth functions (e.g. invertor mathematical model, energy storage mathematical model), which limit the application of conventional gradient approaches to performing security analysis. In these cases, metaheuristic approaches could be a potential solution and researchers should concentrate on finding the practical cases and problems to exploit the potential of metaheuristics.

Third, previous research works have paid very less attention to the sequence of application of controls when more than one remedial action is required to mitigate constraint violations. For example, if the operator is suggested to implement "re-dispatch" and "partial load shedding" as remedial actions, which one has to be applied first and which one has to be applied second to prevent unwanted dynamics. The improper sequence of the application of controls can lead to dynamically insecure transitions, especially under overstressed operating conditions.

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Appendix A

Test Networks Data

The data for the analysed test networks is divided into three parts: static data, dynamic data and fuel cost and emission data. Static data represents the power flow (bus, branch, generation) data, and is available in references [157, 191, 192]. Dynamic data represents the parameter settings for synchronous machines (Table A.1) with the associated automatic voltage regulator (AVR, Table A.2)) and power system stabilizer (PSS, Table A.3). The dynamic data is used in Chapter 7 to validate the stability of proposed remedial actions. Fuel cost and emission data represent the fuel cost coefficients (Table A.4) and emission coefficients (Table A.5) to compute the dispatch cost as well as emission released by the generators. The modelling information of fuel cost and emission is already mentioned in (3.4) and (3.5).

Table A.1 Synchronous machine dynamic parameters (IEEE 39-bus)

Sr No	Bus No	Base MVA	Xl	Ra	Xd	Xd'	Xd''	Td0'	Td0'	Xq	Xq'	Xq''	Tq0'	Tq0''	H	D0	D1
1	39	1000	0.03	0	0.2	0.06	0.01	7	0.003	0.19	0.08	0.03	0.7	0.005	50	0	0
2	31	1000	0.35	0	2.95	0.697	0.01	6.56	0.003	2.82	1.7	0.03	1.5	0.005	3.03	0	0
3	32	1000	0.304	0	2.49	0.531	0.01	5.7	0.003	2.37	0.876	0.03	1.5	0.005	3.58	0	0
4	33	1000	0.295	0	2.62	0.436	0.01	5.69	0.003	2.58	1.66	0.03	1.5	0.005	2.86	0	0
5	34	1000	0.54	0	6.7	1.32	0.01	5.4	0.003	6.2	1.66	0.03	0.44	0.005	2.6	0	0
6	35	1000	0.224	0	2.54	0.5	0.01	7.3	0.003	2.41	0.814	0.03	0.4	0.005	3.48	0	0
7	36	1000	0.322	0	2.95	0.49	0.01	5.66	0.003	2.92	1.86	0.03	1.5	0.005	2.64	0	0
8	37	1000	0.28	0	2.9	0.57	0.01	6.7	0.003	2.8	0.911	0.03	0.41	0.005	2.43	0	0
9	38	1000	0.298	0	2.10	0.57	0.01	4.79	0.003	2.05	0.587	0.03	1.96	0.005	3.45	0	0
10	30	1000	0.125	0	1.0	0.31	0.01	10.2	0.003	0.69	0.08	0.03	1.5	0.005	4.2	0	0

Xl – leakage reactance, Ra – resistance, D0, D1 – damping

Table A.2 AVR settings (IEEE Type-1) for IEEE 39-bus

Sr No	Bus No	Tr	Ka	Ta	Tb	Tc	Vt	Emin	Emax
1	39	0.01	200	0.015	10	1	1.03	-5	5
2	31	0.01	200	0.015	10	1	1.03	-5	5
3	32	0.01	200	0.015	10	1	1.03	-5	5
4	33	0.01	200	0.015	10	1	1.03	-5	5
5	34	0.01	200	0.015	10	1	1.03	-5	5
6	35	0.01	200	0.015	10	1	1.03	-5	5
7	36	0.01	200	0.015	10	1	1.03	-5	5
8	37	0.01	200	0.015	10	1	1.03	-5	5
9	38	0.01	200	0.015	10	1	1.03	-5	5
10	30	0.01	200	0.015	10	1	1.03	-5	5

Tr – low pass filter time constant; Ta, Tb, Tc – regulator time constant; Vt – terminal voltage, Emin, Emax – lower and upper limit for regulator output

Table A.3 Power System Stabilizer (Multiband) settings for IEEE 39-bus

Sr No	Bus No	G	FL	KL	FI	KI	FH	KH
1	39	1	0.2	30	1.25	40	12	160
2	31	1	0.2	30	1.25	40	12	160
3	32	1	0.2	30	1.25	40	12	160
4	33	1	0.2	30	1.25	40	12	160
5	34	1	0.2	30	1.25	40	12	160
6	35	1	0.2	30	1.25	40	12	160
7	36	1	0.2	30	1.25	40	12	160
8	37	1	0.2	30	1.25	40	12	160
9	38	1	0.2	30	1.25	40	12	160
10	30	1	0.2	30	1.25	40	12	160

G – global gain; FL, FI, FH – frequency of low, intermediate, high frequency band; KL, KI, KH – gain of low, intermediate, and high frequency band

Table A.4 Fuel Cost and Emission Coefficients for IEEE 14 Bus

Bus No	Fuel cost Coefficients			Emission Coefficients		
	a	b	c	$d*10^{-6}$	$e*10^{-6}$	f
1	0.00375	2.00	0	6.49	-555	0.0409
2	0.0175	1.75	0	5.64	-605	0.0254
5	0.0625	1.00	0	4.59	-509	0.0426
8	0.00834	3.25	0	3.38	-355	0.0533
11	0.025	3.00	0	4.59	-509	0.0426
13	0.00375	2.00	0	5.15	-556	0.0613

Table A.5 Fuel Cost and Emission Coefficients for IEEE 30 Bus

Bus No	**Fuel cost Coefficients**			**Emission Coefficients**		
	a	**b**	**c**	**$d*10^{-6}$**	**$e*10^{-6}$**	**f**
1	0.00375	2	0	6.49	-555	0.0409
2	0.0175	1.75	0	5.64	-605	0.0254
5	0.0625	1	0	4.59	-509	0.0426
8	0.0083	3.25	0	3.38	-355	0.0533
11	0.025	3	0	4.59	-509	0.0426
13	0.025	3	0	5.15	-556	0.0613

Table A.6 Fuel Cost and Emission Coefficients for IEEE 39 Bus

Bus No	Fuel cost Coefficients			Emission Coefficients		
	a	b	c	d	e	f
30	0.0064	3.90	0.0064	0.0031	-0.24	10.3391
31	0.0111	3.70	0.0111	0.0031	-0.24	10.3391
32	0.0104	2.80	0.0104	0.0051	-0.41	30.0391
33	0.0088	4.70	0.0088	0.0051	-0.41	30.0391
34	0.0128	2.80	0.0128	0.0034	-0.38	32.0001
35	0.0094	3.70	0.0094	0.0034	-0.38	32.0001
36	0.0099	4.80	0.0099	0.0047	-0.39	33.0006
37	0.0113	3.60	0.0113	0.0047	-0.39	33.0006
38	0.0071	3.70	0.0071	0.0047	-0.40	33.0006
39	0.0193	6.90	0.0193	0.0047	-0.40	36.0001

Table A.7 Fuel Cost Coefficients for IEEE 57 - Bus

Bus No	a	b	c
1	0.07758	20	0
2	0.01000	40	0
3	0.25000	20	0
6	0.01000	40	0
8	0.02222	20	0
9	0.01000	40	0
12	0.03226	20	0

Appendix B

Dynamic Thermal Model of Overhead Transmission Line

B.1 Dynamic Thermal Rating of overhead transmission line (OHTL)

$$q_c + q_r + mC_p \frac{dT_c}{dt} = q_s + I^2 R(T_c) \tag{B.1}$$

B.1.1 Convection Heat Loss Rate per Meter

Forced convection heat loss rate

$$q_{c1} = \left[1.01 + 0.0372 \left(\frac{D\rho_f V_w}{\mu_f}\right)^{0.52}\right] k_f K_{angle}(T_c - T_a) \tag{B.2}$$

$$q_{c2} = 0.0119 \left(\frac{D\rho_f V_w}{\mu_f}\right)^{0.6} k_f K_{angle}(T_c - T_a) \tag{B.3}$$

Natural convection heat loss rate

$$q_{cn} = 0.0205\rho_f^{0.5} D^{0.75} (T_c - T_a)^{1.25} \tag{B.4}$$

B.1.2 Radiated Heat Loss Rate per Meter

$$q_r = 0.0178 D\varepsilon [\left(\frac{T_c + 273}{100}\right)^4 - \left(\frac{T_a + 273}{100}\right)^4] \tag{B.5}$$

B.1.3 Conductor electrical resistance

$$R(T_c) = \left[\frac{R(T_{high}) - R(T_{low})}{T_{high} - T_{low}}\right] (T_c - T_{low}) + R(T_{low}) \tag{B.6}$$

B.2 Linearization of OHTL Thermal Model

B.2.1 Convection Heat Loss

$$q_c = K_c (T_c - T_a) \tag{B.7}$$

where

$$K_c = \max(k_{c1}, k_{c2}, k_{cn}) \tag{B.8}$$

$$k_{c1} = \left[1.01 + 0.0372 \left(\frac{D\rho_f V_w}{\mu_f}\right)^{0.52}\right] k_f K_{angle} \tag{B.9}$$

$$k_{c2} = 0.0119 \left(\frac{D\rho_f V_w}{\mu_f}\right)^{0.6} k_f K_{angle} \tag{B.10}$$

$$k_{cn} = 0.06478\rho_f^{0.5} D^{0.75} \tag{B.11}$$

B.2.2 Radiated Heat Loss Rate

$$q_r = K_r(T_c - T_a) \tag{B.12}$$

Where

$$K_r = D\varepsilon(0.0233 + 0.0003T_a) \tag{B.13}$$

B.3 Linearized Thermal Model

According to [204] [205], Eq. (B.1) is linearized and formulated as Eq. (B.14).

$$mC_p \frac{dT_c}{dt} + K(T_c - T_a) = I^2 R(T_a) + q_s \tag{B1.14}$$

where

$$K = K_c + K_R - I^2 \left[\frac{R(T_{high}) - R(T_{low})}{T_{high} - T_{low}}\right] \tag{B.15}$$

B.3.1 Steady-state Conductor Surface Temperature

$$T_c = T_a + \frac{q_s + I^2 R(T_a)}{K} \tag{B.16}$$

B.3.2 Transient Conductor Surface Temperature (After a Step-change of line current)

$$\frac{T_{cf} - T_c}{T_{cf} - T_{ci}} = e^{-\frac{t}{\tau}} \tag{B.17}$$

Where T_{cf} and T_{ci} are steady-state conductor surface temperatures with final line current and pre-change line current. The time constant τ is given as:

$$\tau = \frac{mC_p}{K} \tag{B.18}$$

B.4 Integration of OHTL thermal model as OPF constraints

B.4.1 Normal Operation

In normal state, a maximum temperature limit T_{cmaxO} is applied to steady-state conductor surface temperatures. This temperature limit can be transferred to a current limit as (B.19).

$$I \leq \sqrt{\frac{(K_C + K_R)(T_{cmax} - T_a) - q_s}{R(T_{cmax})}} \tag{B.19}$$

B.4.2 Post-contingency Operation

With a given post-contingency maximum temperature limit T_{cmaxt}, the maximum allowable operating time (or lead time) to reach this temperature is given as:

$$leadtime = -\tau \ln[\frac{T_{cf} - T_{cmaxt}}{T_{cf} - T_{ci}}] \tag{B.20}$$